From Climate Stress to Systemic Vulnerability: Evidence from India

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Abstract

This study examines the impact of climate risks on systemic risk. We use the greenhouse gas emission intensity as key proxy for climate risk. The significant and economical positive relationship is stronger for firms of larger size and higher leverage. Using channel analysis by credit default swap, and internal carbon price confirms that climate risk operates through risk mechanisms. The result is robust to difference -in-difference analysis (DID), system GMM, instrumental variable approach and Heckman two-stage model. It supports that different dimension of climate risks and carbon tax amplifies firms' exposure towards systemic risk. Robustness checks using delta conditional value at risk (*DCoVaR*) and climate adjusted systemic risk (*CRISK*) further validate the findings. It also integrates El Nino index and carbon tax to highlight different aspects of climate risks.

***Keywords*:** Climate risk, Physical risk, Transition risk, DCoVaR, CRISK, ICP, Carbon Emission

JEL Classification: *C36, E44, G30, G32, Q54*

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1. Introduction

In the 21st century, the relationship between climate risk and systemic financial risk has remained unclear. The extreme events related to unexpected changes in temperature can lead to events such as heatwaves, sea level rise, urban flooding, biodiversity loss, etc., and can act as a threat to the whole economic, social, and financial system soon (Luangaram et al., 2026). These interconnected risks can lead to economic instability, high financial volatility, food and water scarcity, and increased migration through physical, transitional litigation and regulatory risks (Chava, 2014).

Systemic risk resulting from climate change is a multifaceted risk arising from the interdependence, exchange, and spontaneous evolution of various individual risks, with its primary characteristic being cascading impacts (Dziwok & Szczepaniak, 2025). The magnitude of risk transmission and its persistence are contingent upon the attributes of the discrete risks that collectively constitute systemic risk. Earlier in the systemic risk literature has recorded that oil prices can create systemic risk in the foreign currency exchange market. The climate stress can have a negative impact on the financial stability and could contribute to financial systemic risk adversely (Klomp, 2014).

Particularly in developing countries, the increasing frequency and intensity of climate-related disasters have raised concerns about systematic risk in financial markets. Systemic risk, sometimes exacerbated by linked exposures and feedback systems, is the possibility that the failure of one or more institutions could cause the whole financial system to collapse (Battiston et al., 2021). Temperature shocks—fast deviations from accepted climatic norms—cause a major physical climate risk that affects operational expenses, supply networks, and corporate productivity (Ai and Gao, 2023). Concurrently, Environmental, Social, and Governance (ESG) performance is seen as a strategic response to climate change concerns rather than only as a measure of corporate accountability. Although ESG investments are expected to shield businesses from environmental disturbances, their effectiveness under highly stressed conditions of climate is yet to be known. Recent studies show that even companies

with strong ESG performance could have higher running costs during severe physical hazards like heat waves, therefore compromising the expected risk-reducing ability of ESG (Cerqueti et al., 2023; Wang et al., 2023). This paper intends to investigate the combined effect of ESG ratings and temperature variations on both firm-specific and systemic risk, therefore supporting the growing area of climate finance and offering policy-relevant insights for sustainable investment frameworks (Battiston et al., 2018).

Notwithstanding the increasing focus on climate-related financial concerns, numerous research deficiencies persist. The influence of climate stress on systemic risk remains under-researched. The literature of climate finance has predominantly concentrated on firm-specific vulnerabilities or sectoral vulnerability and inadequately examined the transmission of climate stress to systemic risk within financial markets (D'Orazio, 2025). This disparity highlights the necessity for additional empirical research that incorporates climate variables into systemic risk modelling frameworks. The study about the role of extreme temperatures on the systemic risk is at a nascent stage (Tzouvanas et al., 2019).

There is a notable gap in the emerging climate finance literature regarding the impact of climatic shocks on the systemic risk in the emerging economies (Lamperti et al., 2021). The diverse climate structure and economic framework would provide great insights which could be explored further (Venturini,2022). Earlier literature on the climate stress highly focused on the developed economies (Dziwok & Szczepaniak, 2025). The study through empirical would contribute on the discuss the relationship between temperature shocks and systemic risk on developing economies.

This study makes several significant contributions to the emerging literature of climate stress and systemic risk. Firstly, this study explores the climate-related systemic financial risks (SFRs), with a primary focus on quantifying transition risk within the broader financial ecosystem. Secondly, it introduces an innovative systemic climate risk indicator, the climate exposure *CoVaR*, which is derived from Adrian and Brunnermeier's (2016) framework. Thirdly, the proposed study would measure how the climate stress occurring from physical and

transition risk can be transmitted to the financial system by integrating firm level ESG performance with the climatic shocks and its financial performance. Additionally, we also use credit default swap (*CDS*) spread and probability of default (*PD*) to validate the findings.

Our study adds to the finance literature in multiple ways. Firstly, our study contributes to the field of climate finance that provides comprehensive view on impact of climate risk on firm performance. By exploring different aspects of climate risk, examining the unique regulatory framework faced by Indian corporate houses, our study enhances this group of literature by investigating the effect of climate risk on firm performance. Our research shows the negative impact of climate risk on firm performance. Furthermore, this relationship strengthens for firms with higher leverage, weak supply chains, higher earnings volatility, higher emission of greenhouse gas (GHG), higher financial constraints and of lower size. Secondly, the earlier empirical work on climate risk discounts the role of ENSO (El Nino Southern Oscillation) and robust supply chain of firms (Addoum et al., 2020; Deng et al., 2025). Earlier paper finds no significant impact of climate risk on firm performance (Addoum et al., 2020; Homroy, 2023). Secondly, we also contribute to this literature on emerging market (Chaudhry and Kumari, 2024; Ding et al., 2024; Zhang and Kong, 2025) by showing firms with higher emission of GHG are more affected by climate risk as in emerging countries, where the climatic variability is more frequent. Thirdly, earlier paper includes single variable for climate risk (Addoum et al., 2020; Bolton and Kacperczyk, 2021; Somanathan et al., 2021), we along with climate risk, explore physical and transition risk to provide a more comprehensive view regarding climate risk. Fourthly, as a novelty, we also explore new dimensions of climate risk such as carbon tax and ICP, which is completely discounted in earlier literature of climate finance (Bolton and Kacperczyk, 2023). Fifthly, we also investigate the impact of twin threat of climate risk on firm performance to complement the study of (Borsuk et al., 2026) via the interaction of different dimension of climate risk.

We also incorporate ENSO index (*EN*) and internal carbon price *(ICP*) as valid and relevant proxy that drives regional temperature, precipitation and emission levels respectively. We have also address firms' heterogeneity through firm size and firm leverage. Earlier paper like Addoum et al. (2023) and Huang et al. (2018) explore only one dimension of climate risk in supply chain mechanism and cash flow volatility/earning volatility respectively. We explore physical risk and transition risk dimension for the internal carbon price framework and probability of default along with firms' credit default spread premium. Additionally, we extend the SRISK approach of Acharya et al. (2017) and Brownlees and Engle (2017) to non-financial firms.

The remainder of the paper is structured as follows. Sections 2 discuss the literature review and hypothesis development, Section 3 provides framework for data collection, Section 4 discusses the research methodology, Section 5 provides empirical results, Section 6 discuss the additional tests and robustness tests, and Section 7 provides the conclusion for the empirical paper. Appendix I provides the description of the variables used in the paper.

2. Literature Review and Hypothesis Development

The existing literature explores textual mining, media coverage analysis and corporates earning call reports to measure climate risk, but such methodology is subject to reporting biases, noisy and often capture perceptions regarding climate risk. It also helps to ensure the empirical evidence is rooted in observable climate dynamics rather than analysis of words mentioned in the media or news reports.

2.1 Climate Risk and Systemic risk

Luangaram et al. (2026) investigate the relationship between carbon emission and financial stability for emerging markets. It uses market-based measures like *CoVaR* (conditional value at risk) to calculate systemic risk. It shows that transition risk amplifies systemic risk exposure for financial firms in the Thailand financial market. It measures physical climate risk through Standardized Precipitation Evapotranspiration Index (SPEI). Differential return between environmentally. D'Orazio (2025) investigates the effectiveness of climate

related financial policies with respect to financial stability for banking sector of 88 countries. It documents that stronger financial resilience associated with stronger climate related policies. It observes that insurance sector is more vulnerable to climate sector due to more stress on capital buffer, reduces its financial resilience.

Battiston et al. (2021) explores the role of systemic climate risk on its financial implications. It observes that climate risk affects long run financial stability, arising from climate related events. Similarly, Lamperti et al. (2021) shows firms observe losses in the financial assets due to volatility in climate related events such as: droughts, flood, heatwave, etc. It uses Dystopian Schumpeter meeting Keyne (DSK) model to model systemic risk. Dziwok and Szczepaniak (2025) investigate the role of extreme climate stress on systemic risk. It calculates climate betas using GJR-DCC-GARCH model to capture its time varying nature. It extends SRISK model N-RISK model to eight US systemically important banks. It founds transition climate betas to be positive as increase in stranded assets amplifies exposure to systemic risk. Likewise, the physical climate betas are negative as highly volatility temperature profile negatively affects banks financial resilience.

Siddique et al. (2021) and Liu et al. (2023) argue about the positive link between greenhouse gas emission and environmental performance and carbon disclosure. They observe that firms improve their environmental performance to offset the rising carbon emission. They explore legitimacy theory as investors rewards firms with carbon disclosure as license to operate in the society (Battiston, 2019; Han et al., 2023; Siddique et al., 2021). Earlier studies also focused on the relationship between equity market risk and greenhouse gas emission such as (Alessi et al., 2021; Aswani et al., 2024; Bolton and Kacperczyk, 2021; Reboredo and Ugolini, 2022). They argue carbon premium quite underpriced in the equity market. Griffin et al. (2017) founds a significant negative relation between firm level emissions and stock prices as the firm with higher carbon emission would face litigation and reputational risk, more regulatory intervention as well as it signals negative perception for the investors.

Very few literatures are available for the role of climate risk on systemic risk in emerging markets (Park et al., 2020; Xue et al., 2026). Wang et al. (2026) investigate the impact of climate risk on cash holding of firms. It was found that post Paris Agreement, there is increase in cash reserve, influenced by perception of climate risk. Xue et al. (2026) investigate climate transition risk and energy companies in China. It finds that climate risk increases the stranded assets for firms in the coal, electricity and oil and gas industry. Zhang and Kong (2025) found that climate risk affects firms operating cost positively, thereby it affects firm performance negatively. Similarly, Jung et al. (2018) observe that with increasing climate risk, there is increasing cost of debt in the emerging countries. Similarly, Tran et al. (2024) find thar climate risk increases firms distress risk which influence firm performance negatively.

Based on the above literature, we have formulated the following hypothesis

H1: Climate risk affects systemic risk positively.

2.2 Alternative aspect of Climate Risk

To explore different aspect of climate risk, we also consider physical risk and transition risk.

In the previous climate finance literature has explored the natural language processing to study the evolving role of media to increase the public awareness regarding environmental issues. (Ardia et al., 2023; Engle et al., 2020) role of US media in capturing the climate change, using two major newswires: Associated Press Newswires and Reuters News. It has followed the framing theory of (Chong and Druckman, 2007) to study the use of informational content by the media.

Engle et al. (2020) develops two monthly indices to measure the climate risk using Wall Stret Journal articles and some climate change vocabulary extracted from authoritative text of climate change. It does not distinguish between physical and regulatory risk arising from climate change. The paper has also explored the firm level ESG score to proxy the exposure to climate change risk. Criterion and King (2023) discusses about the link between environmental, social and governance and systemic risk EU-28 member states for the period of 2012-2019. It

has employed the delta conditional value at risk (*CoVaR*) introduced by (Adrian and Brunnermeier, 2016) based on the value at risk model on panel data of 362 commercial banks. The higher values of CoVaR would indicate higher interconnectedness between the firms and higher overall systemic financial risk. It has used 4 models environmental, social, governance, and ESG (combined) models to reflect the contribution of banks into the systemic financial risk. In the banking sector too, the positive link between systemic risk and implementation of environmental issues observed (Gangi et al., 2021).

The prudent behaviour of the banks would reduce their exposure to the systemic financial risk and can be translate as positive externalities. Climate change is already considered as a threat to financial stability by the regulatory authorities (BIS,2021; ESRB, 2021). The transmission channels for the climate change would consists of physical risks (rising sea levels, severe weather events such as flood), transition risks (uncertainty in the cash flows regarding the transition to the clean energy) and liability risks (compensations delivered to the economic agents due to materialisation of physical or transition risk).

The increasing recognition of climate risks (CRs) as a driver of systemic financial risks (SFRs) has led to a growing body of research that explores their implications for financial stability. Climate-related risks, both physical and transition-related, have the potential to destabilize financial markets and amplify systemic vulnerabilities (Battiston et al., 2018; Diluiso et al., 2021; Lemoine, 2021; Network for Greening the Financial System, 2021). However, while much of the existing literature examines the relationship between climate risks and financial risks more broadly (Bouri et al., 2022; Dhifaoui et al., 2023; Ren et al., 2023; Bua et al., 2024; Tedeschi et al., 2024). There is comparatively limited research focusing on the specific interplay between CRs and SFRs (Benoit et al., 2017; Corsi et al., 2018). Given the diverse nature of climate risks and their potential to serve as catalysts for financial instability, there is an urgent need for deeper investigations into how climate-induced systemic financial risks evolve across different market conditions and policy environments.

Recent research has attempted to bridge this gap by analysing the nonlinear dynamics between CRs and SFRs. While previous studies have established links between climate risks and financial instability newer frameworks emphasize the need for advanced methodologies to quantify systemic risks more effectively. This includes developing climate-specific risk indicators and integrating climate-related shocks into systemic risk assessment models. Furthermore, the literature underscores the importance of differentiating between various types of climate risks, particularly climate physical risk (CPR), climate transition risk (CTR), and climate policy uncertainty (CPU) (Yan and Cheung, 2023; Zhu et al., 2023). These studies highlight that climate policy uncertainty, arising from abrupt regulatory changes or inconsistent government policies, is a key driver of financial market volatility and systemic risk exposure.

Empirical evidence from Chinese financial markets provides valuable insights into the association between CRs and SFRs. Studies employing Granger causality tests, regression models, and regime-switching analyses suggest that the linear causal relationships between CRs and SFRs are often weak or insignificant, whereas nonlinear causal associations are statistically robust (Tian and Li, 2024). Specifically, CPR and CTR exhibit notable nonlinear causality with systemic risks, while CPU-induced uncertainties exacerbate financial instability. The bidirectional causal relationship between CTR and financial stability further supports the argument that transition risks—such as stranded assets, carbon pricing mechanisms, and regulatory shifts—can amplify systemic vulnerabilities in financial markets (Campiglio et al., 2023; Sun et al., 2023; Delis et al., 2024). This reinforces the need for policy coordination to mitigate financial instability arising from climate transition risks.

Another key aspect of the literature concerns the macroeconomic consequences of climate-induced SFRs. Research suggests that elevated levels of climate-related systemic financial risks have a significant negative impact on macroeconomic stability. The revaluation of carbon-intensive assets, for instance, often leads to mispricing and market inefficiencies, while extreme weather events result in economic losses through infrastructure damage and production disruptions (Ren et al., 2022; Dong et al., 2024; Zhu et al., 2025). Furthermore,

empirical studies indicate that financial regulators respond to heightened systemic financial risks with policy interventions, as evidenced by government efforts to stabilize markets through financial regulations and fiscal policies (Curcio et al., 2023). However, the uncertainty surrounding climate policies introduces additional instability, making it difficult for investors and financial institutions to price risks accurately.

The role of climate-related events in shaping financial stability has also been a major focus of contemporary research. Climate crises and extreme weather events are found to have significant but heterogeneous effects on financial markets, with market reactions influenced by crisis severity, investor sentiment, and policy credibility (Ma et al., 2024). Studies suggest that major public emergencies, including natural disasters and extreme climate events, tend to amplify systemic financial risks by triggering sudden shifts in capital flows and asset valuations. Moreover, the unidirectional causality from climate risk communication to systemic financial risks highlights the importance of investor perception and information dissemination in shaping market dynamics.

Collectively, the literature underscores the growing need for financial markets to integrate climate risks into risk assessment frameworks. Given the increasing frequency and severity of climate shocks, financial institutions and regulators must develop adaptive models that incorporate both direct and indirect climate-related risks. While existing studies provide foundational insights into the connections between climate risks, systemic financial risks, and macroeconomic stability, further research is needed to refine quantitative climate-financial risk models and develop policy mechanisms that enhance financial resilience. As the global financial system continues to evolve in response to climate challenges, the need for a comprehensive, forward-looking approach to climate-related systemic financial risks remains paramount.

Wang et al. (2024) provides empirical evidence on the impact of environment, social and governance (ESG) performance on the systemic risk exploiting the publicly listed 284 Chinese firms for the period from 2011 to 2020. It has included sectors from energy, metals,

finance etc. The papers have introduced the tail risk spillover network to draw the systemic risk among the firms. The paper has concluded that higher ESG performance significantly reduce the systemic risk within the corporate network as firm with better ESG performance would be better tackle the threat posed by the climate change (Xue et al., 2025). Aevoae et al. (2023) has explored the relationship between corporate social responsibility and systemic risk across 47 countries and 367 publicly listed banking institutions. To measure the corporate social responsibility, it has taken the ESG performance as the proxy variable. It has the sample data for the period of 2007 to 2020. It has studied the impact of ESG combines score on the systemic risk, observed that the impact is driven by governance pillar score. It has concluded that firms' governance performance has significant role in mitigating the systemic risk contributions. It has observed that in the context of large banks and emerging economies there is increasing in systemic risk even with higher ESG combined score, as the emerging economies faces challenges related to environmental practices, disclosure norms, enforcement of workforce rights,

Cerqueti et al. (2021) investigates the relationship between ESG compliance and systemic risk across the network of mutual funds. It has used the sample period from 2016 to 2018 to understand the interconnectedness between mutual funds houses and their contagion effects. It has calculated the loss of market value for the top 20% and below 20% funds based on ESG score. It was observed that funds having higher ESG score has relatively less loss of market value than funds with lower ESG score. It has exploited the network analysis and financial contagion theory. R. Bauer et al. (2007) observed that there is no significant difference between performance of ethical mutual funds compared to their conventional peers. It has concluded that imposition of ethical conditions does not adversely affect the returns for the investors. El Ghoul and Karoui, (2017) investigates how the corporates social responsibility affects mutual funds' performance. It was cited that investment in socially responsible and environmentally sustainable projects would constraints the number of projects available as well as would increase monitoring cost. It would adversely affect the funds performance. The

increase in the level of socially responsible and ethically governed investments would reduce firm value. It has also observed that the cash flow sensitivity decreases with increasing socially responsibility of the funds.

Bax et. al. (2023) studies the interdependence between ESG score and risk profile of 330 United States companies for the period from 2007 to 2021 with more emphasis on the tail dependence. The paper has employed R vine copula modelling to observe the dependence structure of the firms for a particular ESG rating class. The researchers assign rating A for the ESG scores between 75 to 100, rating B for the scores between 50 to 75, rating C for scores in the range of 25 to 50, and D for the range of 0 to 25. It was observed that ESG score are directly relate to risk profile of a firm especially the tail risk, reflect that ESG score can influence the negative returns. The papers argues that ESG rating can also acts as a valuable indicator to measure a company's vulnerability to systemic shocks in the economy.

Based on the above literature, we formulate the following hypothesis

H2: Transition Risk affects systemic risk positively.

H3: Physical Risk affects systemic risk positively.

3. Data

The financial data and data regarding plants and factories of firms are collected from $Prowess_{dx}$ database. The data for temperature and precipitation is collected from the Ministry of Earth Science (MoES) and Indian Meteorology Department (IMD) respectively at district or sub-state (district) level following the approaches of Venturini (2022), Ai and Gao (2023), and Pankratz and Schiller (2024). Data related to greenhouse gas emission and carbon emission is collected from Refinitiv workspace. The score of climate risk index (*CRI*) is collected from Germanwatch annual reports. The project level data are extracted from Capexdx database of CMIE (Centre for Monitoring Indian Economy). We have excluded financial firms as they have distinct rules and regulation (Flannery and Rangan, 2006; Avezum et al., 2022). The sample period for the paper is 2010 to 2024 to measure physical risk and transition risk. The data of greenhouse gas emission is available from 2016 to 2024 to measure climate risk. In India the

regulations for greenhouse gas emission (GHG) evolved after 2015.[1] Furthermore, the climate action of India to achieve net zero is also become explicit in 2015.[2] A total of unique 25,476 firm-year observations from 5,029 firms constitute the final sample. The index of El nino (*EN*) is collected from National Oceanic and Atmospheric Administration (NOAA). The data of probability of default (PD) and credit default swap spread is collected from credit risk initiative (CRI) database of National University of Singapore.

We calculate *COVAR* following the approach of Adrian and Brunnermeier (2016). It captures the changes in the Value at Risk (VaR) of the financial market condition on a distress event affecting firm *i.* We define systemic event when the stock returns (R_i) are in the negative or worst 5% of the annual distribution. VaR refers to threshold return so that the probability of returns being equal or less than is 5%. VaR of firm *i* is calculated as follows:

$$Prob\left(R_i \leq VaR_{i,5\%}\right) = 5\% \quad \text{… (1.1)}$$

Next, we define *CoVaR* (Conditional Value at Risk) of the financial market as the VaR of the financial system condition that firm *i* is in distress. It captures the conditional left tail risk of the financial system, conditional that firm *i*, experience extreme negative outcome. *CoVaR* is interpreted as 5% quantile of the conditional probability distribution:

$$Prob\left(R_m \leq CoVaR_{i|M} | R_i = VaR_{i,5\%}\right) = 5\% \quad \text{… (1.2)}$$

For ease of our interpretation, following Dungey et al. (2022) we multiply *CoVaR* by negative one. It means higher values of *CoVaR* shows higher systemic risk.

[1] https://www.ceew.in/sites/default/files/ceew-impact-of-select-climate-policies-on-indias-emissions-pathway-07nov24-file.pdf

[2] NITI Aayog. (2026). A Study Report On - Scenarios Towards Viksit Bharat and Net Zero: An Overview (Vol. 1).

4. Research Methodology

We measure climate risk using greenhouse gas emission. We bifurcate climate risk into two primary parts of physical risk and transition risk following Venturini (2022). Additionally, we also explore role of carbon tax and internal carbon price in systemic risk. Single measure of climate risk is sufficient but not provide comprehensive picture of climate risk and not cover all dimensions of climate risk.[3]

Physical risk is measured by temperature and precipitation as followed by Balvers et al. (2017), Somanathan et al. (2021), and Addoum et al. (2023). Following Nandy and Lodhi (2012), Venturini (2022), Guo et al. (2024), and Fligel (2026), transition risk is measured though environmental performance.[4] Climate risk is calculated by emission intensity (greenhouse gas emission scaled by net sales), as followed by Bolton and Kacperczyk (2021), Han et al. (2023) and Aharon et al. (2024). Industries are classified based on section level national industrial classification. The data of temperature and precipitation were assigned to factory and plant houses of firms as the factory units are the most affected through physical climate risk (Somanathan et al., 2021; Addoum et al., 2023; Pankratz et al., 2023; Benincasa et al., 2024; Yang et al., 2026). The data of factory and plant units for the firms is available district wise which justifies collecting the climatic variable for each relevant district.

Many studies follow different approach to calculate climate risk. A large number of studies construct climate risk index by using Google search indexes and news texts to study the impact of climate change on various types of capital markets (Engle et al., 2020; Faccini et al., 2021; Ardia et al., 2023). Climate risk impacts the level and volatility of earnings in publicly listed companies, with firms in countries with higher climate risk holding more long-term debt and cash while paying lower cash dividends (Huang, Kerstein, and Wang, 2018). Sautner et al. (2023), and Kölbel et al. (2024) also exploits natural language processing (NLP) to calculate

[3]https://www.ecgi.global/publications/blog/carbon-emissions-and-bank-lending-a-green-shift-or-just-greenwashing

[4] Pricing of climate risks in financial markets: a summary of the literature, BIS Papers No. 130 (Bank for International Settlements, Dec. 2022).

firm level climate risk from earning call reports, 10-K reports. Some studies such as Chava (2014), and Nandy and Lodh (2012) use environmental scores and environmental performance as measure of climate risk. At the country level, Hong et al. (2019) use the Palmer Drought Severity Index (PDSI), considering temperature and soil moisture, to measure climate risk. Earlier papers such as Bernstein et al. (2019), Burnside et al. (2016) uses natural disaster data to measure climate risk. Earlier literature such as Huang et al. (2018), and Zhao and Parhizgari (2024) use the climate risk index (*CRI*) as indicator for climate risk. *CRI* is published by Germanwatch as an annual score for economic losses based on the temperature shocks and volatility in perception levels. At the country or regional level, Bernstein et al. (2019), and Alok et al. (2020) uses the economic losses caused by disasters for the regions or counties where US firms are located to measure climate risk. Pankratz et al. (2023) also used the temperature anomaly as per the firm's head-quarter location to measure climate risk. Pankratz and Schiller (2024) further used temperature and water-level changes to measure climate risk. Koetter et al. (2020) uses temperature anomalies at city level to measure climate risk. Hsu et al. (2023) considers the sulphate toxics emissions from various industrial clusters, creates a long-short portfolio to measure climate risk. However, such indicators are subject to certain limitations, such as non-applicability to firm level, often not cover various dimensions of climate risk and few studies measure climate risk at firm or corporate level (Zhang and Kong, 2025).

We use the pooled OLS regression to test the formulated hypothesis with following equations:

$$CoVaR_{i,t} = \beta_0 + \beta_1 X_{i,t} + \beta_2 SIZE_{i,t} + \beta_3 MTB_{i,t} + \beta_4 ROA_{i,t} + \beta_5 LEV_{i,t} + \beta_6 OCF_{i,t} + \beta_7 PPE_{i,t} + \beta_8 CASH_{i,t} + \vartheta_j + \delta_t + \epsilon_{i,t}$$

… (1.3)

In the Equation (1.3) *X* refers to *PERCP* and *TEMP* as physical risk, *ENV SCORE* for transition risk, *GHG INT* for climate risk, *EN* for el-nino and *CRI* for climate risk index. To capture direct, immediate and tangible impact of climate risk we use physical risk. Transition

risk would capture regulatory as well as investor perception of climate risk. El nino (*EN)* would capture the short-term climatic disturbances that can trigger heatwaves, droughts etc. For firm *i* and year *t,*. *CoVaR* represents the 5% Value at Risk of firm igiven that the financial system or market portfolio experience extreme downside conditions, *ESG SCORE* is the environmental, social and governance performance score, *ENV SCORE* represents environmental performance score of firms, *SOC SCORE* indicates social performance score of firms, *GOV SCORE* is the governance score of firms, *GHG INT* is the emission intensity derived from greenhouse gas emission*, PERCP* is the average precipitation per year*, TEMP* is defined as the yearly average temperature in ^{0}C, *CRI* is the score of climate risk index published by Germanwatch*, SIZE* is defined as the natural logarithmic of market value of equity, *MTB* shows the ratio of market to book value of equity, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets *LEV* is defined as ratio of debt to equity, *OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. Equation (1.3) measures physical risk, transition risk and climate risk including year and industry fixed effect. To treat for heteroscedasticity, standard errors were clustered by firm. In Equation (1.3) ϑ_j, and δ_t shows the industry and year fixed effect respectively. We use industry fixed effect to capture the difference across industries.

5. Empirical analysis

5.1 Descriptive statistics

Panel A of Table 1 shows the descriptive statistics of *TEMP, ENV SCORE, GHG INT by* industry. Panel B reflects the descriptive statistics by year. Panel C descriptive statistics of *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets*;* Panel D shows the spearman correlation matrix of variables used in the study. Panel A shows that the transport infrastructure industry has higher mean *TEMP* of 55.497, means it has higher exposure to physical risk (*TEMP*). Similarly, automobile industry has mean *ENV SCORE* of 14.605, shows that it is highly vulnerable to transition climate risk (*ENV SCORE*).

Likewise, chemical and transport infrastructure industry is highly vulnerable to climate risk as it has the mean *GHG INT* of 3.193 and 4.872 respectively.

Panel B shows that year 2010 and 2017 associated with maximum and minimum *ENV SCORE* respectively. Year 2012 has maximum mean *ENV SCORE* of 6.791 and year 2016 has minimum *ENV SCORE* of 3.959. Maximum mean climate risk (*GHG INT*) is observed in the year of 2024 is 5.852 and minimum mean *GHG INT* is observed in the year 2021 of 2.166 influenced by nationwide lockdowns due to COVID-19. It is clearly observed in figure 1. Similarly, in figure 2 minimum mean *TEMP* is observed in the year 2010 of 20.317^0 C due to moderate La Lina event. Maximum mean *TEMP* is observed in the year 2023 of 43.408^0 C due to the impact strong El nino event.

Similarly, panel D of Table 1 that *TEMP, PERCP, ENV SCORE, GHG INT* are positively related to *CoVaR.*

[Insert Table 1 here]

[Insert Figure 1 here]

[Insert Figure 2 here]

5.2 Regression results

Table 2 reports the results of baseline regression Eq. (1.3). Column (1) shows the impact of climate risk. It supports our primary hypothesis that climate risk affects systemic risk positively.

Column (1) shows that a standard deviation increase in *GHG INT* would positively affect the systemic risk by 2.8%. Also, the positive impact of *GHG INT* on the systemic risk is statistically significant at the 1% level. Column (2) shows that climate risk affects the systemic risk positively, when controlling for industry by year fixed effects. It means the baseline result remains unchanged when we control for industry specific trend through industry-year fixed effect. It shows that a standard increase in climate risk positively affect the systemic risk by 9.2 percentage points. Column (3) address the cross-sectional dependence through Fama Macbeth

regression. It also holds the positive relationship between climate risk and systemic vulnerability of Indian firms. Economically, a standard deviation increases in climate risk positively affect the systemic risk by 3.9 percentage.

It is observed in the Column (5) that serial correlation or heteroskedasticity do not materially affect the statistical significance of positive relationship between climate risk and systemic risk. To explore whether the positive relationship between climate risk and systemic risk is driven by manufacturing firms, we divide the sample into manufacturing and non-manufacturing firms. The positive coefficient of *GHG INT* in the Column (6), and (7) is statistically significant at the 1% level, suggests that climate risk positively affect the systemic risk regardless of industry classification of firms. Column (6) shows that for firms belongs to manufacturing industry; a standard deviation increase in *GHG INT* would positively affect the systemic risk by 10.3%.

We also observe the impact of carbon tax (*CTAX*) on systemic risk. Union Budget of 2016-17 increased the coal cess (Clean Environment Cess) to Rs. 400 per tonne to finance National Clean Energy and Environment Fund (NCEEF).[5] Later it is subsumed under GST compensation cess but the rate of Rs. 400 per tonne remained same until its discontinuation in 2024.[6] This policy aligns with the firm level emission data from 2016 to 2024 to capture the financially relevant phase of climate risk. It helps to transform the variable of carbon emission to the angle of financial cum climate cost. We construct the carbon tax exposure, scaled by firms' net sales to ensure comparability across firms of different sizes. It shows the negative impact of carbon tax on firms' performance at the 1% statistical significance level. Column (8) shows the positive impact of carbon tax (*CTAX*) on systemic risk. Economically, a standard deviation increases in climate risk increase systemic risk by 1.71 percentage points. In Column

[5] https://doe.gov.in/files/circulars_document/NCEF_Brief_post_BE_2017_18.pdf (Ministry of Finance, Government of India.)
[6] Carbon Pricing in Practice: A Review of the Evidence. Medford, MA. Climate Policy Lab, The Fletcher School, Tufts University.

(8) we also control for VaR (value at risk) to account for individual tail risk. The baseline regression results stay the same. The coefficient on climate risk is positive and statistically significant at 1% level. It shows that climate risk has economical and statistically significant impact on systemic risk, independent of firm specific risk factors.

The missing values of *GHG INT* addressed through imputation techniques (Kofman and Sharpe, 2003; Chen and McCoy, 2024). Using median imputation method of Freiberg et al. (2020), the missing value of GHG INT are replaced through median values of industry-year values. Specifically, we use the control variables in Eq. (1.1) to predict *GHG INT*. Using single imputation method, it is observed in Columns (10) that the coefficients on *GHG INT* are statistically significant at the 1% level.

In Column (11), we also control for *EPU* (economic policy uncertainty) to check that systemic risk is independent of macro-economic shocks. The coefficient on *GHG INT* is still positive and statistically significant at the 1% level. It shows that the positive impact of climate risk on systemic risk is not driven by macro-economic shocks.

[Insert Table 2 here]

6. Additional tests

6.1 Endogeneity test

6.1.1 Two stage least squares (2SLS) estimation

Additionally, we address the endogeneity concern through second stage lease square method. The primary requirement for 2SLS is that the valid instrument should meet the exogeneity as well as relevance condition. For the relevance condition, the instrument should be correlated with the endogenous variable (*GHG INT*). Similarly, for the exogeneity condition, the instrument variable should not be correlated with the error term of structural equation model and should not directly influence the dependent variable of interest.

Following Homroy (2023), we instrument the climate risk through lagged, industry average values of average climate risk (IV_1) and upstream Scope 3 emission (IV_2) (excluding the focal firm for both instruments). Through this approach, industry level scope 3 emissions

capture industry wide production technologies used by the supplier orthogonal to firm level performance. We anticipate that, firm with higher emissions of scope 3 emissions would have higher emissions of greenhouse gases.

Column (1) and (2) of panel B Table 3 reports the results of first and second stage regression of second stage least square estimation (2SLS). In the first stage, two instrument variables (IV_1 and IV_2) are regressed on climate risk (*GHG INT)* using Eq. (1). The coefficient on both the instruments is significant at the 5% level, suggests that scope 2 and scope 3 emission influence climate risk. Further, the fitted values of *GHG INT* are used to estimate Eq. (1.1) in the second stage. The coefficient on the climate risk *GHG INT* is statistically significant at the 1% level. The positive coefficient on the Column (2) shows that climate risk significantly affects systemic risk. It estimates from the second stage least square estimate address the endogeneity concerns associated with omitted variable bias.

Furthermore, to check the consistency of the 2SLS estimation, we have also done some diagnostic tests. Panel D of Table 3 reports the diagnostic results from the second stage least square estimation. The 1% level statistical significance of Wooldridge robust regression F-test statistics (1, 468) of 8.745 shows that climate risk (*GHG INT*) is an endogenous variable. To check whether we also do Cragg and Donald (1993) test. The value of F (2,468) statistic is 7.900 and statistically significant at the 1% level. It shows that instrument variables are not weak. Similarly, an insignificant score of 0.079 and 0.042 on the Saragn $\chi 2$ and Basmann $\chi 2$ test statistics shows that the model is not over specified.

6.1.2 Difference in Difference Analysis

Table 3 shows the difference in difference analysis for green firms (firms with lesser greenhouse gas emissions). The *ENV SCORE* was divided into two quantiles based on industry median. Firms in the lower 50% of the distribution were labelled as '*BROWN*', and those in the upper 50% were labelled as '*GREEN*' as followed by Bua et al. (2024). Paris Agreement, a legally binding international treaty, signed in November 2015 to reduce emission of greenhouse gases (GHG). We use Paris Agreement as an exogeneous event influencing performance of

firms having higher environmental score. Fligel (2026) also found that firms with higher emission intensity have higher environmental score.

Panel A reports the summary statistics for both treatment and control firms. The difference between means and medians of treatment and control firms are not statistically significant. It shows that treatment and control firms are not significantly differ across the matching variables. *GREEN* firms were treated firms and *BROWN* firms were controlled firms. *POST PARIS* is the period after the Paris Agreement of 2015. It shows that *POST PARIS, BROWN* (control group) firms have contributed positively towards systemic risk, but *Treat* (GREEN) firms contribute negatively towards systemic risk quite consistent with Table 3. Similarly, *GREEN* group of firms also face positive impact of climate risk on systemic risk, consistent with the shareholder theory and ESG investing theory as explained earlier and in aligned with studies of Han et al. (2021), and Nguyen et al. (2023). The results of DID also suggests that post Paris Agreement, *TREAT* (GREEN) firms contribute negatively towards systemic risk.

The parallel trend of *ROA* of treatment and control firms is shown in Figure 3. It shows that the exogeneous shock of Paris Agreement, both the treatment and control firms show same parallel trend. But the Paris Agreement of 2015, consistent rise of *ROA* is observed for the treatment firms than for the control firms.

6.1.3 Placebo Test

Furthermore, we run a placebo test to test whether false treatment timing shows an effect. For the placebo test, actual treatment year 2015 is replace by 2019 (*POST2*) with two-year pre and post event window (2017 - 2021). The Placebo interaction term is expected to be insignificant as there is no Paris Agreement related shock in 2019. Column (4) of Table 3 reports the placebo test. The insignificant interaction between *TREAT* and *POST2* supports additional evidence that negative impact of climate risk on systemic risk of *TREAT* firms is not

driven by time trend. It can be concluded that, the negative impact of systemic risk for green (*TREAT*) firms after the year 2015 is attributable to the event of Paris Agreement.

6.1.4 Heckman test

Furthermore, to evaluate that our sample selection is not influenced by non-random selection process, we also use Heckman 2 stage process. The results are shown in Column (5) and Column (6) of Table 3. We first model the likelihood of firms included in the Eq. (1.3) based on the firm's characteristics used in the Eq. (1.1). From first stage equation, it gives the inverse mill ratio (*IMR*). *IMR* is incorporated in the second stage regression to adjust for self-selection bias. The coefficient on *IMR* is statistically non-significant, confirming that the positive relationship between climate risk and systemic risk is robust.

6.1.5 System GMM (generalized methods of moments)

To address endogeneity, we have followed the system GMM to address the problem of endogeneity. Following Arellano and Bond (1991), Siddique et al. (2021), and Nguyen et al. (2023) the first lag of dependent variable is treated as instrument variable to address the concern of endogeneity. The results are reported in the Column (7) of Table 3.

To check whether the model is consistent, we also perform various diagnostic tests. Panel E of Table 3 reports the diagnostic results from the Arellano and Bond System GMM. We conduct the Hansen (1992) J test to check the crucial assumptions that instruments are valid as well as not endogenous. Panel Table 3 also reports the results of diagnostic test (Hansen test). The value of Hansen test (0.602), failed to reject the null hypothesis of insufficient exogeneity at 1% significance level. It also reflects that identification strategy is valid and not affected by endogeneity. Column (9) of Table 3 shoes the results of system GMM.

[Insert Table 3 here]

6.2 Alternative measures of climate risk

To capture different aspects of climate risk such as physical risk, transition risk, el-nino, we also use different variables for the same. The coefficient on the *TEMP* and *PERCP* is statistically significant at the 1% and 5% level respectively for physical climate risk. For

physical climate risk *TEMP* and *PERCP,* we use district fixed effect as the data for them are collected at district level. It helps to control for time invariant district characteristics.

The coefficient on *ENV SCORE* is statistically significant at the 5% for transition risk. From the result of Table 4 it was observed that increasing a standard deviation of *ENV SCORE* would increase systemic risk by 1.54%. Similarly, a standard deviation increase in *TEMP* would increase systemic risk by 0.34%, a standard deviation increase in *PERCP* would increase systemic risk by 5.2%. It supports our second and third hypothesis that physical risk and transition risk affect systemic risk positively.

In column (4) we explore climate risk index from Germanwatch *CRI* following Ben Abdesslem et al. (2025), Bolton and Kacperczyk (2023), and Huang et al. (2018). For *CRI* following Arian and Naeem (2025), and Huang et al. (2018) we multiply the climate risks index score (*CRI*) by negative one so that higher climate risk index score indicates higher climate risk. It is observed that a standard deviation increases in *CRI* increase firms exposure to systemic risk by 3.5%. Similarly, Column (5) shows that in the period of el nino (*EN*), firms exposure towards systemic risk by 3% when the standard deviation of *CRI* increases by one. Table 4 reflects the results of climate risk using different alternative measures.

[Insert Table 4 here]

6.3 Simultaneous risk exposure

To capture the impact of twin threats of climate risk on systemic risk (when firm exposed to different climate risk simultaneously), we interact between different measures of climate risks in Table 5 by following Borsuk et al. (2026). In Column (1) it is observed that both physical and climate risk (*TEMP* × *GHG INT*) positively impact systemic risk. The positive coefficient on the interaction (*TEMP* × *GHG INT*) shows physical risk accelerate the positive impact of climate risk on systemic risk.

Also in Column (2), and (3) the impact of *ENV SCORE* (transition risk) is positive on systemic risk when there is non-existence of physical risk and climate risk as environmental

performance disclosure is related to higher short-term regulatory and compliance burden, investors pressure for decarbonisation and adaption cost (Chava, 2014). It is observed that higher environmental disclosure of firms realised in long run when there is a existence of physical and climate risk as noted by Fligel (2026).

Similarly, Column (2) shows the interaction of $TEMP \times ENV\ SCORE$, shows that in the presence of transition risk, physical risk amplifies positive effects on the systemic risk. Likewise, in Column (3) the interaction $GHG\ INT \times ENV\ SCORE$ shows transition risk amplifies the positive impact of climate risk on systemic risk. The result of any of the variable does not overturn the result of baseline regression reported in Table 2. The impact of simultaneous risk exposure is reported in Table 5.

[Insert Table 5 here]

6.4 Role of probability of default (*PD*)

We also explore the role of probability of default as transmission mechanism for climate risk with reference to systemic risk. Higher values of *PD* represent higher systemic risk. We examine the role of probability of default both in short run (one month, three months, and six months) and long run (one year, three year and five year). In Column (1) it is observed that increase in climate risk, increases the one-month probability of default by 0.050 basis points. The coefficient on climate risk is statistically significant at the 1% level. Economically, it means the one standard deviation increase in climate risk, increase the probability of default by 0.70 basis points. The positive relationship is not changed from Column (2) to (6).

In Column (7) it is observed that firm's probability of default amplifies the effect on *CoVaR.* The coefficient on *PD* is positive and statistically significant at the 1% level. It shows that chances of default intensify firms' exposure to systemic risk.

It shows that carbon intensive firm appear to be more vulnerable to systemic risk. The results are reported in Table 6.

[Insert Table 6 here]

6.5 Firm Heterogeneity

We observe firm heterogeneity by firm size and firm leverage.

6.5.1 Firm Size

Table 7 shows the role of firm size (*SIZE*) and leverage (*LEV*) of firms on climate risk, physical risk and transition risk.

We bifurcate the full sample into two parts based on above and below median industry firm size (*SIZE*). Column (1) to (3) shows the positive role of larger firms in relation to climate risk and systemic risk. From Column (1) to Column (3), the coefficient on climate risk, physical risk and transition risk is positive and statistically significant at the 1% level. It shows that large firms are not only more exposed to systemic risk due to more capital base but also amplifies the impact of climate risk. The statistically significant positive coefficient on column (2) shows that larger firms in the period of higher transition risk, more exposed to systemic risk. Similarly, Column (3) shows that larger firms fail to offset the positive impact of physical climate risk (Pastor et al., 2021).

From Column (4) to (6), the coefficient on climate risk, physical risk and transition risk is negative and statistically significant at the 1% level. It shows that small firms are not much exposed to systemic risk compared to firms of large size.

6.5.2 Leverage

We bifurcate the full sample into two parts based on above and below median industry firm leverage (*LEV*). From Column (7) to (12) of table 7 shows the effect of firms leverage in relationship between climate risk and systemic risk.

Column (7) to (9) of Table 7 shows the effect of higher leverage in relationship between climate risk and systemic risk. The coefficient on climate risk, physical risk and transition risk is positive and statistically significant at the 1% and 5% level respectively. Specifically, firms with higher leverage experience exacerbation in performance declines with rising temperature shocks and greenhouse emission as greater debt obligation pose as obstacle to transit to low

carbon economy. Higher leverage amplifies the vulnerability for firms to face the challenges introduced by climate risks as well as physical risk. It is observed that firms with more external dependence are more vulnerable to negative effects of climate risk (more expose to systemic risk), therefore such firms more exposed to systemic vulnerability related to climate risk

Conversely, Column (10) to (12) shows positive role of climate risk for firms with lower leverage. The coefficient on climate risk, physical risk and transition risk is negative and statistically significant at the 10% and 5% level respectively. Column (10) shows that lower financially risk firms help to mitigate the systemic risk of the financial system. Similarly, Column (11) to (12) shows that physical and transition risk, negatively affect for firms with lower leverage. It shows that lower leverage firms are more resilient to different dimensions of climate risk. Typically, lower leverage firms have higher investment capacity to transit towards low-carbon economy (Narula et al., 2024). The results are reported in Table 7.

[Insert Table 7 here]

6.6 Brown and green firms and climate commitment policy

We also explore the role of brown and green firms and firms' commitment to reduce investment in carbon intensive activities in the relationship between climate risk and systemic risk. We expect that firm with lower emissions (green firms) and with commitment to reduce investment in carbon intensive projects are negatively contributed towards systemic risk.

6.6.1 Brown and green firms and phaseout of carbon intensive investment

To address firm level heterogeneity, we divide the firms based on greenhouse gas emission (*GHG INT*) into brown and green following Andersson et al. (2016), Bolton and Kacperczyk (2023), and Hsu et al. (2023) on 50^{th} percentile or median (two groups). Firms in the lower 50% of the distribution were labelled as '*GREEN*', and those in the upper 50% were labelled as '*BROWN*'.

Table 8 investigates the link between climate risk, physical risk and systemic risk for *BROWN* and *GREEN* firms. Column (1) and (2) reflects that brown firms are the most affected by physical and transition risk. The coefficient on the interaction terms is also statistically significant at 5% level, as carbon intensive firms are more vulnerable to abnormal temperature shocks through operational inefficiency. In Colum (1) and (2) shows that transition risk and physical risk affect systemic risk positively for *BROWN* firms.

Similarly, Column (3) and (4) indicate that firms with less emission of greenhouse gas are insulated from physical risk as well as transition risk due to dynamic capabilities framework and environmental capabilities. In Colum (3) and (4) shows that transition risk and physical risk affect systemic risk negatively for *GREEN* firms. The investments in cleaner technologies, innovation and climate conscious strategies are paid off for green firms to mitigate the positive effect of physical risk as well as transition risk. The results are reported in Table 8.

6.6.2 Phaseout of carbon intensive investment

We also explore firms' commitment to reduce its investment in carbon intensive projects. *PHASEOUT* is a dummy variable. It takes value one when the firm is committed to reduce its carbon footprint else the value is zero.

Column (5) of table 8 shows that systemic risk (*CoVaR*) of firms with the commitment to reduce carbon footprint are negatively affected by climate risk. Similarly, Column (6) shows that climate adjusted systemic risk (*CRISK*) of firms with commitment to reduce carbon footprint are negatively affected by climate risk. Since firms with such commitment are subject to low regulatory burden and stranded assets, and exposed to lower climate risk premia (Pastor et al., 2021; Bolton and Kacperczyk, 2023)

[Insert Table 8 here]

It shows that firms with higher emissions of GHG are positively affected by climate risk, physical and transition risk compared to firms with lower emission of GHG. Similarly, firms with a climate commitment policy to reduce carbon footprint are negatively exposed to

systemic risk compared to firms without such policy. Firms with climate commitment often shows stronger positive sensitive to climate risk.[7]

6.6 Additional Analysis

We explore channel analysis by credit default swaps, and internal carbon price (*ICP*). Emission intensity reduction and *ICP* capture firms' response towards and exposure towards climate risk. It helps to provide more comprehensive and detailed picture of climate risk. We infer that credit default swaps act as transmission mechanism for climate risk.

6.6.1 Corporate default swaps

We also explore the role of credit default swap as transmission mechanism for climate risk with reference to systemic risk. *CDS* spreads refers to the premium paid to compensate against the default risk of the reference firm. Higher values of CDS represents higher systemic risk. In Column (1) it is observed that increase in climate risk, increases the one-year credit default swap spread by 0.050 basis points. The coefficient on climate risk is statistically significant at the 1% level. Economically, it means the one standard deviation increase in climate risk, increase the credit default risk spread by 0.70 basis points. The positive relationship is not changed from Column (2) to (5).

In Column (6) it is observed that firm's credit default swap spread amplifies the effect on *CoVaR.* The coefficient on *CDS_1Y* (1 year period) is positive and statistically significant at the 1% level. It shows that higher credit risk intensifies firms exposure to systemic risk.

It shows that carbon intensive firm appear to be more vulnerable to systemic risk. The results are reported in Table 9.

[Insert Table 9 here]

6.6.2 Climate related scenario analysis

[7] Carbon Pricing Leadership Coalition (2017): Report of the High-Level Commission on Carbon Prices

This sub-section examines the relationship systemic risk and climate risk related scenario analysis (*CRS*) conducted by firms. *CRS* is a dummy variable, takes the value of one if a firms conduct climate related analysis else zero.

Column (3) to (4) of Table 10 shows the negative impact of firm's exposure to systemic risk with respect to conduction of climate risk analysis. Column (3) shows that climate adjusted systemic risk (*CRISK*) is negative affected by climate risk, as such firms anticipate climate risk in advance, thereby reduce its exposure to downside tail risk. Similarly, Colum (4) shows that systemic risk of firms with climate risk analysis (*CoVaR*) is negatively associated with firms level climate risk.

6.6.3 Internal carbon price

Internal carbon price is a managerial discipline that enhance the efficiency of resource allocation. Very few studies explore the *ICP* as part of climate risk.[8] Column (1) and (2) examines the impact of internal carbon pricing (*ICP*) on firm's systemic risk. Firms with *ICP* expects future carbon price regulation through carbon credit, carbon tax or other similar instruments. *ICP* is a dummy variable, it has value one if company assigns a value to emission of greenhouse gas or else zero. Firms following internal carbon pricing signal their readiness for potential regulatory and policy shocks. In Column (1) and (2) the coefficient on the *ICP* is negative and statically significant at the 1% level.

Colum (1) shows that firms with internal carbon pricing or shadow pricing, negatively expose to climate adjusted systemic risk as firm with internal carbon price, includes carbon cost in their investment decision and lower level of stranded assets. Similarly, Column (2) shows that firms with shadow carbon pricing through *ICP,* expose to systemic risk negatively.

It suggests that *ICP* plays the role of internal hedging instrument against regulatory, decarbonisation pressure and technology advancement. Firms exploit *ICP* as a forward-looking approach to transition climate risk. The results are reported in Table 10.

[8] Desjardins, M., Gianfrate, G., Ghitti, M., and Sinclair-Desgagne, B. (2024). Internal carbon pricing – A price instrument to cope with organizational failure (*FEB-RN Research Paper No.* 59/2025).

[Insert Table 10 here]

In Table 11 it is observed that systemic risk of firms integrating climate risk into the corporate decision framework through internal carbon price are not necessarily positively affected by climate risk. Such firms can convert the challenges of climate risk into opportunities through investment in cleaner technologies.[9]. It also suggests that internal carbon price as risk management tool helps firms to face the challenges posed by climate risk.[10]

6.7 Robustness test

To further test the robustness of our findings, in table 11 we use *CRISK* and *DCoVaR* (delta CoVaR) as proxy for systemic risk. We calculate *CRISK* following the approach of Jung et al. (2025). We measure *DCoVaR* as follows:

$$DCoVaR_{system|i} = CoVaR_{system|R_i=VaR_{i,5\%}} - CoVaR_{system|R_i=VaR_{i,50\%}} \quad \ldots (\mathbf{1.4})$$

For ease of our interpretation, following Dungey et al. (2022) we multiply *DCoVaR* by negative one. It means higher values of *DCoVaR* shows higher systemic risk. Column (1) and (3) shows that climate risk increase firms exposes towards both climate adjusted systemic risk (*CRISK*) and *DCoVaR.* Similarly, Column (2) and (4) shows that transition risk affect amplifies firms' systemic vulnerability positively.

Column (6) to (7) we also use *SPEI* (standardized precipitation evapotranspiration index) as proxy for precipitation shocks for physical climate risk. It shows that during heighten precipitation; firms are more exposed to systemic risk. During the periods of precipitation shock, the infrastructure as well as supply chain is disrupted, which exposed firms to more financial distress (Pankratz and Schiller, 2024).

[Insert Table 11 here]

[9] Carbon Pricing in Practice: A Review of the Evidence. Medford, MA. Climate Policy Lab, he Fletcher School, Tufts University.
[10] CDP (2017): Putting a price on carbon - Integrating climate risk into business planning.

7. Conclusion

Our findings confirm that the baseline relationship between climate risks and systemic risk is predominantly positive: both physical climate risk as proxied by temperature anomalies and precipitation level, and transition risk proxied by environmental performance score (*ENV SCORE)*, exhibit positive associations with systemic risk. The results are consistent with prior evidence that environmental shocks and carbon exposure erode operational efficiency and financial outcomes (Chava, 2014; Hsu et al., 2023). Larger firms due to larger capital base and carbon intensive assets, more exposed to systemic risk. In contrast, high financial leverage exacerbates vulnerability of firms to climate risk and its different components, aligning with the prior evidence that debt constraints amplify exposure to adverse shocks (Krueger et al., 2020; Ginglinger and Moreau, 2023; Sautner et al., 2023). For firms and investors, rising temperature shocks in the climate system would not only amplify uncertainty but also make financial system more volatile. Exploiting Germanwatch climate risk index (*CRI*) as proxy for climate risk confirms that firms are vulnerable to systemic risk in the period of climatic shock (Arian and Naeem, 2025; Bolton and Kacperczyk, 2023; Huang et al., 2018).

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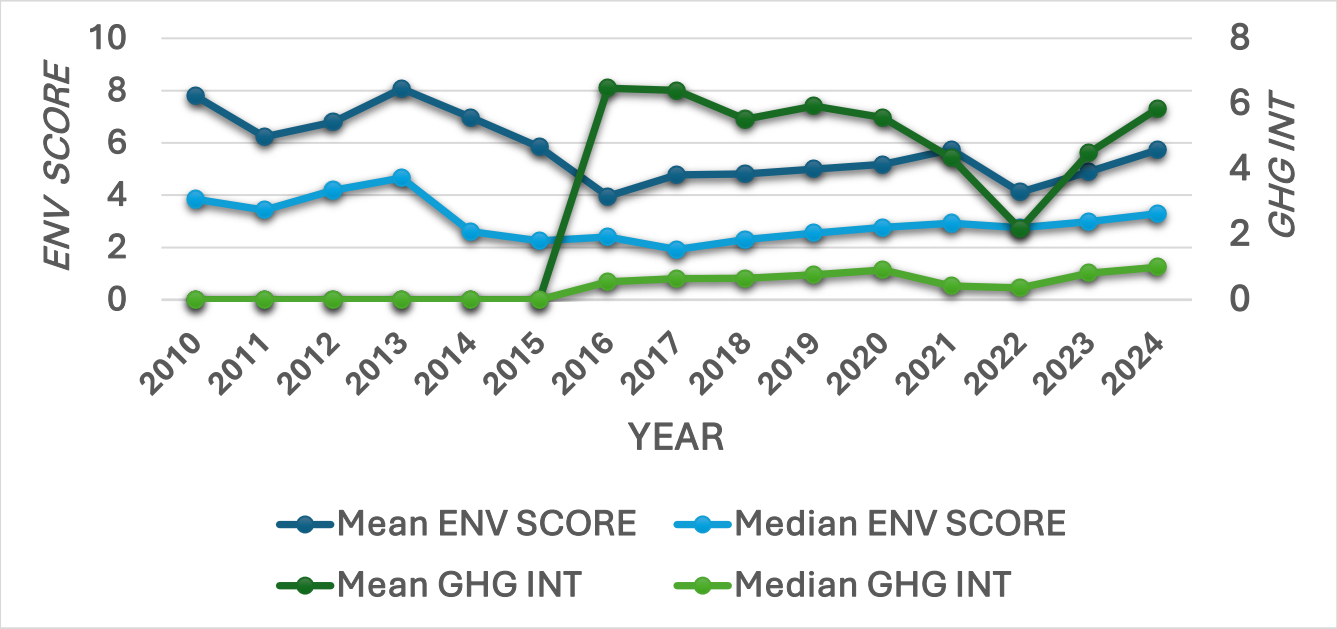


Figure 1. Trend for mean and median *GHG INT* and *ENV SCORE* expenditure.

This figure plots the mean and median values of climate risk (*GHG INT*) and transition risk (*ENV SCORE)*. The sample period is from 2010 to 2025. The left (right) hand side axis represents the scale for mean and median *GHG INT (ENV SCORE). GHG INT* is the emission intensity derived from greenhouse gas emission per unit of net sales. *ENV SCORE* is the transition risk, represents firms' environmental performance score

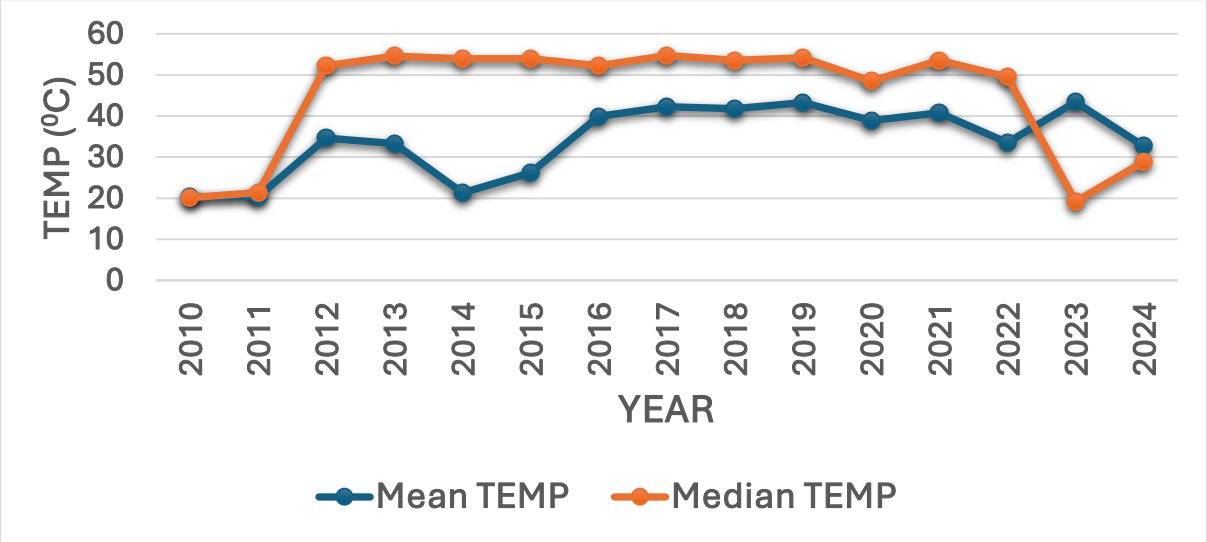


Figure 2. Trend for mean and median *TEMP*.

This figure plots the mean and median values of *TEMP* (in ^{0}C). The sample period is from 2010 to 2024. The left-hand side axis represents the scale for mean and median *TEMP* (^{0}C). *TEMP* is the physical climate risk, defined as the yearly average temperature in ^{0}C.

Table 1: Descriptive Statistics

Panel A: This panel reports the sample distribution by industry.

ENV SCORE represents firms' environmental performance score, *TEMP* is defined as the yearly average temperature in ^{0}C. *GHG INT* is the emission intensity derived from greenhouse gas emission. Column (1) reports the number of observations, Columns (2), (3) and (4) reports mean and median *ENV SCORE, TEMP* and *GHG INT* respectively. Columns (5), (6) and (7) reports mean and median *ENV SCORE, TEMP* and *GHG INT* respectively. All variables are winsorized at the 1st and 99th percentile. The sample period is from 2010 to 2024.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
		Mean	Mean	Mean	Median	Median	Median
		ENV		*GHG*	*ENV*		
Industry	N	*SCORE*	*TEMP*	*INT*	*SCORE*	*TEMP*	*GHG INT*
Aerospace and Defence	441	5.972	27.171	0.010	1.982	2.590	0.006
Automobiles	365	14.605	37.558	0.250	16.128	46.762	0.015
Building Products	437	3.578	38.367	0.036	1.511	48.214	0.014
Chemicals	991	4.967	39.743	3.193	3.036	53.300	0.021
Communications Equipment	151	3.789	38.523	0.007	1.279	47.068	0.007
Construction and Engineering	1,344	4.386	46.463	0.190	1.742	53.563	0.009
Construction Materials	537	7.675	36.351	0.937	4.921	26.160	0.127
Diversified Telecommunication Services	109	7.179	44.746	0.008	6.118	48.458	0.005
Electrical Equipment	1,026	4.282	37.952	0.029	1.426	46.762	0.011
Gas Utilities	560	14.056	32.619	0.074	11.950	21.705	0.049
Health Care Providers	108	4.109	49.362	0.006	1.117	54.356	0.003
Hotels, Restaurants and Leisure	505	4.703	34.422	0.011	2.929	24.974	0.008
IT Services	655	4.364	46.197	0.004	1.201	53.857	0.002
Machinery	653	3.785	36.626	0.024	1.391	25.425	0.015
Metals, Oil and Mining	412	4.832	37.631	0.075	2.153	41.412	0.048
Paper and Forest Products	339	5.695	37.693	0.023	5.127	46.762	0.027
Pharmaceuticals	911	5.233	41.471	0.010	2.282	53.300	0.007
Software	491	3.211	45.943	0.003	1.067	53.447	0.002
Textiles	254	3.900	42.556	0.012	2.283	54.231	0.004
Tobacco	145	10.026	39.576	0.027	4.727	47.610	0.003
Transportation Infrastructure	122	6.775	55.497	4.872	5.122	55.134	0.033

Panel B: This panel reports the sample distribution by year.

	(1)	(2)	(3)	(4)	(5)	(6)
	Mean	Mean	Mean	Median	Median	Median
	ENV		*GHG*	*ENV*		
Year	*SCORE*	*TEMP*	*INT*	*SCORE*	*TEMP*	*GHG INT*
2010	7.791	20.317	-	3.841	20.126	-
2011	6.239	20.422	-	3.424	21.387	-
2012	6.791	34.591	-	4.183	52.262	-
2013	8.076	33.289	-	4.659	54.551	-
2014	6.981	21.269	-	2.608	53.94	-
2015	5.843	26.186	-	2.256	53.915	-
2016	3.959	39.911	6.473	2.397	52.243	0.551
2017	4.781	42.243	6.404	1.922	54.72	0.651
2018	4.815	41.756	5.524	2.299	53.586	0.654
2019	4.994	43.245	5.925	2.551	54.159	0.765
2020	5.18	38.923	5.579	2.768	48.458	0.91
2021	5.745	40.775	4.337	2.922	53.563	0.424
2022	4.116	33.548	2.1662	2.75	49.535	0.358
2023	4.900	43.408	4.492	2.993	19.182	0.815
2024	5.733	32.674	5.852	3.295	28.864	0.995

Panel C: This panel reports the summary statistics of all variables used in the study .
ROA is defined as operating profit before interest and taxes scaled by book value of total assets, *TobinsQ* is computed as market value of equity plus long-term debt plus current liabilities scaled by book value of assets, *CRI SCORE* is the climate risk index published by Germanwatch,. *ESG SCORE* is the environmental, social and governance performance score, *ENV SCORE* represents environmental performance score of firms, *SOC SCORE* indicates social performance score of firms, *GOV SCORE* is the governance score of firms, *GHG INT* is the emission intensity derived from greenhouse gas emission, *PERCP* is the average precipitation per year, *TEMP* is defined as the yearly average temperature in ^{0}C, *SIZE* is defined as the natural logarithmic of book value of total assets, *LEV* is defined as ratio of debt to equity, *SGROWTH* is the growth rate of net sales, *OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *INTANG* is the ratio of intangible assets and total assets, *CASH* is firms cash holding scaled by total assets, *SCM* is the composite supply chain measure integrate supply chain policies as well as practices, *EN* is the index for el nino. All continuous variables are winsorized at the 1st and 99th percentile. The sample period is from 2010 to 2024.

	(1)	(2)	(3)	(5)	(6)
	Mean	Median	SD	Min	Max
CoVaR	0.052	0.050	0.014	-0.133	0.049
GHG INT	30.671	15.224	13.965	1.958	87.044
TEMP	21.864	21.772	3.610	2.000	41.284
ENV SCORE	10.335	8.571	7.852	0.000	77.535
PERCP	130.625	67.467	4.414	63.549	83.594
SIZE	7.822	7.003	12.620	19.07	160.822
MTB	13.240	14.910	5.451	8.970	26.160
ROA	0.101	0.061	12.133	-250.000	2037.000
LEV	1.916	0.000	18.407	-0.093	164.000
OCF	0.006	0.183	5.009	-23.20	27.62
PPE	6.785	6.788	2.884	2.303	15.263
CASH	0.010	0.023	0.046	0.010	1.000
CRI SCORE	21.980	17.97	9.013	3.870	58.482
EN	0.427	0.102	0.320	0.000	1.437
DCoVaR	0.051	0.050	0.015	-0.171	1.913
CRISK	0.404	0.493	1.023	0.303	0.737

Panel D: This panel represents spearman correlation matrix.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1) CoVaR	1.000																		
(2) ROA	-0.176*	1.000																	
(3) ESG SCORE	0.288*	0.395*	1.000																
(4) ENV SCORE	0.612*	-0.557*	0.212*	1.000															
(5) SOC SCORE	-0.244*	0.216*	0.183*	0.184*	1.000														
(6) GOV SCORE	-0.214*	0.171*	0.048*	0.221*	-0.061*	1.000													
(7) GHG INT	0.071*	-0.084*	0.034*	-0.265*	-0.112*	0.737*	1.000												
(8) TEMP	0.140*	-0.126*	-0.038*	0.150*	0.031*	0.605*	0.600*	1.000											
(9) PERCP	0.210*	0.144	0.014*	0.236*	-0.057*	0.674*	0.338*	0.361*	1.000										
(10) SIZE	0.046*	-0.015	-0.080*	-0.055*	0.024	-0.001	-0.007	0.004	-0.019	1.000									
(11) MTB	-0.013*	0.008	0.003	-0.009	-0.037*	0.043*	0.019*	0.008	0.041*	0.059	1.000								
(12) OCF	0.029*	0.030*	0.016*	0.030*	-0.019*	0.069*	0.043*	0.015*	0.058*	0.010	0.574*	1.000							
(13) DCoVaR	0.224*	0.150*	0.096*	0.227*	-0.127*	0.628*	0.577*	0.369*	-0.358*	0.035	- 0.014*	0.067*	1.000						
(14) PPE	-0.034*	-0.030*	0.060*	-0.043*	-0.012*	-0.075*	-0.018*	-0.064*	-0.076*	0.001	0.006	-0.020*	-0.005	1.000					
(15) LEV	0.042*	0.010*	-0.001	0.038*	0.011*	0.008	0.003	0.006	0.007	0.002	-0.004	-0.021*	0.032*	-0.018*	1.000				
(16) CASH	-0.061*	-0.081*	-0.030*	-0.075*	0.068*	-0.009	0.105*	-0.094*	-0.085*	0.024	0.100*	-0.094*	0.057*	0.022*	0.019*	1.000			
(17) CRISK	0.136*	0.098*	0.062*	0.110*	0.063*	0.512*	0.584*	0.301*	0.234*	0.085*	-0.076*	0.004	0.819*	0.001	0.030*	0.435*	1.000		
(18) CRI SCORE	0.050*	-0.021*	-0.012*	-0.065*	-0.024*	-0.026*	0.010	-0.016*	-0.023*	-0.025	0.034*	-0.025*	-0.052*	-0.002	0.135*	0.015*	0.040*	1.000	
(19) EN	0.002*	-0.004	0.015*	-0.002	0.019*	-0.015	0.058*	-0.087*	0.001	0.009*	-0.001	0.003	-0.001	-0.011	0.003	0.128*	0.491*	0.048*	1.000

Table 2: **Baseline regression model with industry and year fixed effect**

CoVaR is the dependent variable, *GHG INT* is the greenhouse gas emission scaled by net sales, *SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity, *OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets, *CTAX* denotes carbon tax. All continuous variables are winsorized at the 1st and 99th percentile.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Baseline regression	Industry by year FE	Cluster standard error by firm and year	Fima and Macbeth (1973) regression	Newey and West (1997) standard errors	Manufacturing firms	Non-manufacturing firms	Carbon tax	Controlling for *VaR* (value at risk)	Single imputation	Controlling for EPU (economic policy uncertainty)
GHG INT	0.002***	0.001**	0.001***	0.002***	0.001**	0.001***	0.001***		0.002***	0.001***	0.001***
	(3.977)	(2.455)	(3.511)	(3.888)	(.708)	(3.981)	(5.756)		(3.777)	(4.877)	(5.459)
CTAX								0.001***			
								(6.240)			
VaR									1.097***		
									(18.000)		
EPU											0.001**
											(2.872)
SIZE	0.001**	0.003***	0.001*	0.001*	0.001	0.001*	0.003***	0.001*	0.001***	0.001**	0.001**
	(2.808)	(4.513)	(2.257)	(1.937)	(0.493)	(1.802)	(4.660)	(1.740)	(5.780)	(3.808)	(2.532)
MTB	-0.540***	-0.619***	-0.540***	-0.540**	-21.563*	-0.547**	-0.569***	-0.168**	-0.009***	-0.570***	-0.001
	(-3.523)	(-4.877)	(-4.444)	(-4.518)	(-3.760)	(-2.530)	(-4.619)	(-4.119)	(-8.719)	(-4.623)	(1.552)
ROA	-0.477**	-0.583**	-0.477*	-0.477**	-0.225	-0.475**	-0.245	-0.958***	0.045***	-0.147**	0.024***
	(-2.308)	(-2.257)	(-1.927)	(-2.401)	(-0.276)	(-2.300)	(-1.265)	(-4.601)	(4.265)	(-2.908)	(5,875)
LEV	-0.001	-0.001*	-0.001	-0.001	-0.001**	-0.001	0.001	-0.001*	-0.001*	-0.001	-0.001
	(-1.005)	(-1.958)	(-1.025)	(-0.865)	(-1.924)	(-1.004)	(0.278)	(-1.818)	(-1.978)	(-1.105)	(-0.598)
OCF	-0.001	0.001	-0.001	-0.001	0.007	-0.001	-0.001	-0.001**	-0.001*	-0.001	-0.001***
	(-0.676)	(0.767)	(-0.440)	(-0.599)	(0.705)	(-0.692)	(-0.970)	(-2.388)	(-1.770)	(-0.996)	(-3.908)
PPE	0.001**	-0.000	0.001**	0.001***	0.000	0.001**	-0.001	0.001*	-0.001	0.001**	0.001**
	(2.511)	(-1.001)	(2.877)	(2.656)	(1.407)	(2.519)	(-0.726)	(1.921)	(-0.726)	(2.845)	(2.153)
CASH	-0.116***	0.044***	-0.116**	-0.116***	-0.049***	-0.116***	-0.045***	-0.058	-0.145***	-0.116***	-0.123***
	(-3.035)	(8.593)	(-3.474)	(-3.009)	(-4.710)	(-3.037)	(-9.819)	(-0.412)	(-6.819)	(-3.945)	(-4.238)
Constant	-0.096	-0.110***	-0.096	-0.091	-1.635	-0.096	-0.106**	-0.072	-0.106**	-0.096	-0001***
	(-0.035)	(-7.593)	(-0.074)	(-0.009)	(-0.710)	(-0.037)	(-0.879)	(-0.874)	(-0.415)	(-0.475)	(-11.098)
Industry FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry - Year FE	No	Yes	No	No	No	No	No	No	No	No	No
N	1,726	1,661	1,726	1,733	1,227	423	1,303	1,480	1,726	1,726	1,712
Adj. R^2	0.477	0.494	0.497			0.479	0.520	0.475	0.459	0.417	0.498

Table 3: **Endogeneity test through Difference-in-Difference (DID) Analysis**

CoVaR is the dependent variable, *L1* is the lagged of dependent variable (*CoVaR*), *TREAT* is green firm, *TREAT*POST PARIS* is the variable of interest, *POST PARIS* is the period after Paris Agreement, *GHG INT* is the greenhouse gas emission scaled by net sales, *SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity, *OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. All continuous variables are winsorized at the 1st and 99th percentile.

Panel A: This panel presents results from the tests of difference-in-means and difference-in-medians for the control and treatment firms for variables used for matching control and treatment firms for the benchmark year of Paris Agreement (2015)

	(1) Mean	(2) Median	(3) Mean	(4) Median	(5)= (3) – (1) in means	(6)= (4) – (2) in medians
CoVaR	0.056	0.059	0.060	0.065	0.004	0.006
ENV SCORE	0.474	0.370	5.143	5.664	4.666***	-5.294***
SIZE	5.754	5.838	8.187	8.426	2.433	2.588
MTB	2.112	2.009	1.711	1.325	-0.401**	-0.684*
OCF	0.019	0.022	0.014	0.045	-0.005	0.023
SGROWTH	0.210	0.147	0.259	0.222	0.049	0.075
PPE	4.135	3.483	7.163	7.499	3.028	4.016
ROA	0.078	0.005	0.052	0.004	-0.026	-0.001
CASH	0.032	0.041	-0.031	-0.047	-0.063**	-0.088*

Panel B: This panel presents results from the tests of difference-in-means and difference-in-medians for *CoVaR* before and after the Paris Agreement (2015)

	(1) Pre Paris Agreement Mean	(2) Pre Paris Agreement Median	(3) Post Paris Agreement Mean	(4) Post Paris Agreement Median	(5)= (3) – (1) Differences in means	(6)= (4) – (2) Differences in medians
R1 Control firms	0.055	0.052	0.057	0.060	0.002	0.008
R2 Treatment firms	0.053	0.064	0.061	0.065	0.008	0.001
R3 Difference in Means/Medians (R2-R1)	-0.002	0.012	0.004	0.005		

Panel C: This panel presents results from the tests of difference-in-means and difference-in-medians for *ENV SCORE* before and after the Paris Agreement (2015)

	(1) Pre Paris Agreement Mean	(2) Pre Paris Agreement Median	(3) Post Paris Agreement Mean	(4) Post Paris Agreement Median	(5)= (3) – (1) Differences in means	(6)= (4) – (2) Differences in medians
R1 Control firms	0.480	0.041	0.473	0.358	-0.007	0.317
R2 Treatment firms	5.378	6.898	5.843	4.711	0.465	-2.187
R3 Difference in Means/Medians (R2-R1)	4.898***	-6.857***	5.370	4.353		

Panel D: This panel represents the results from the diagnostic tests for 2SLS estimation

Test of endogeneity
H0 = Variables are exogenous
Robust regression F (1, 468) = 11.745 (p = 0.000)

Test of weak instruments
H0 = Instruments are weak
F (2, 468) = 7.900 (p = 0.001)
Cragg and Donald (1993) test

Minimum eigenvalue statistic = 8828.670
Critical values
H0: Instruments are weak

	5%	10%	20%	30%
2SLS Size of nominal 5% Wald test	19.93	11.59	8.75	7.25
LIML Size of nominal 5% Wald test	8.68	5.33	4.42	3.92

Test for over-identifying restrictions
H0 = Instruments are valid
Sargan χ^2 (p-value) = 0.079 (0.7785)
Basmann χ^2 (p-value) = 0.042 (0.8366)

Panel E: This panel represents the results from the diagnostic tests for Arellano and Bond System GMM estimation

Arellano-Bond test for AR(1) = 1.880 (p = 0.000)
Arellano-Bond test for AR(2) = 0.440 (p = 0.506)

Hansen test χ^2 (p-value) = 26.020 (0.177)

Panel F: This panel reports the results of endogeneity tests including two stage least square estimation, Difference-in-Difference analysis (DID), placebo test, matched sample analysis and heckman test, and Arellano and Bond System GMM.

	(1) 2SLS First stage	(2) Regression Second stage	(3) Difference-in-Difference (DID)	(4) Placebo test	(5) Heckman test (first stage)	(6) Heckman test (second stage)	(7) System GMM Arellano and Bond
L1							0.006***
							(59.452)
GHG INT		3.149**				0.756***	0.134**
		(2.776)				(3.662)	(3.046)
TREAT			0.002**	0.968			
			(1.970)	(1.291)			
POST PARIS			0.001**				
			(3.479)				
TREAT × POST PARIS			-0.002**				
			(-2.497)				
POST2				-0.425			
				(-0.860)			
TREAT × POST2				-0.665			
				(-0.860)			
SIZE	9.456	34.443	0.014***	0.322	0.676***	0.921	8.260**
	(1.498)	(0.248)	(3.414)	(0.379)	(26.370)	(0.269)	(2.593)
MTB	-0.099	-1.761	-0.002***	0.772**	0.004	-0.584	-39.767
	(-0.301)	(-1.642)	(-3.841)	(2.203)	(0.971)	(-0.807)	(-1.397)
ROA	0.399**	-0.215***	-0.024	0.045	0.055	0.646	8.867
	(2.943)	(-5.348)	(-1.338)	(0.111)	(0.571)	(0.741)	(0.453)
LEV	-3.650*	0.984*	-0.083***	0.934	-0.001**	-0.460***	-7.709**
	(-2.417)	(1.645)	(-4.417)	(0.210)	(-5.424)	(7.519)	(-2.899)
OCF	0.038	-0.108***	-0.005*	0.886	-1.083***	-0.877	0.799***
	(0.047)	(-7.524)	(-1.903)	(1.649)	(-4.614)	(-0.616)	(4.149)
PPE	-0.962***	5.001	-0.003	-0.001**	0.094***	-0.134***	0.221
	(-3.306)	(0.530)	(-0.322)	(-2.948)	(5.085)	(-4.771)	(0.284)
CASH	-0.069	-0.576**	0.064*	-0.001**	-0.766***	-0.881	-8.507***
	(-0.592)	(-3.130)	(1.074)	(-2.852)	(-5.664)	(-0.283)	(-4.053)
IMR						0.484	
						(0.559)	
IV_1	0.012***						
	(4.611)						
IV_2	0.118**						
	(2.557)						
Constant	1.882***	7.836	-0.073***	-0.121***	-7.502***	-0.482	0.100**
	(2.681)	(0.098)	(-24.103)	(-8.497)	(-48.083)	(-0.082)	(2.106)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	694	694	5,082	809	600	584	1,060
Adj. R^2	0.414	0.489	0.239	0.432	0.470	0.496	-

Table 4: **Alternative measures of climate risk**

CoVaR is the dependent variable*, ESG SCORE* is the environmental, social and governance performance score, *ENV SCORE* represents environmental performance score of firms, *SOC SCORE* indicates social performance score of firms, *GOV SCORE* is the governance score of firms, *CRI* is the climate risk index*, EN* is the el-nino index, *PERCP* is the average precipitation per year*, TEMP* is defined as the yearly average temperature in ^{0}C, *SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity*, OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. All continuous variables are winsorized at the 1st and 99th percentile.

	(1) Transition risk	(2) Physical risk	(3) Physical risk	(4) Climate risk index	(5) El -nino
ENV SCORE	0.000***				
	(2.764)				
TEMP		0.001**			
		(2.423)			
PERCP			0.001**		
			(2.023)		
CRI				0.001***	
				(7.443)	
EN					0.002***
					(7.928)
SIZE	0.001***	0.002***	0.001***	0.002***	0.002***
	(3.336)	(10.920)	(11.648)	(18.683)	(23.479)
MTB	0.000***	0.001***	0.000***	0.000***	0.000***
	(5.079)	(3.54)	(3.318)	(7.804)	(4.729)
ROA	0.002**	0.006***	0.008***	0.003***	0.003**
	(2.337)	(2.940)	(3.094)	(2.734)	(2.464)
LEV	-0.000	-0.001***	-0.001***	-0.001*	-0.001
	(-1.252)	(-3.301)	(-3.489)	(-1.628)	(-0.826)
OCF	0.001**	-0.001	-0.002	0.000	0.001
	(2.953)	(-0.828)	(-1.431)	(0.253)	(1.224)
PPE	0.001	-0.004**	-0.084**	-0.001***	-0.001***
	(0.559)	(-4.936)	(-1.936)	(-7.572)	(-7.433)
CASH	-0.034	0.005**	0.045**	-0.033	-0.039*
	(-1.207)	(2.900)	(2.064)	(-1.313)	(-1.887)
Constant	-0.061***	0.973***	-0.064***	-0.067***	-0.066***
	(-8.967)	(12.833)	(-22.401)	(-16.416)	(-11.269)
Industry FE	Yes	Yes	Yes	Yes	Yes
Dist FE	No	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
N	6,800	7,020	6,800	7,607	7,607
Adj. R^2	0.662	0.583	0.487	0.619	0.595

Table 5: **Simultaneous risk exposure**

CoVaR is the dependent variable, *ENV SCORE* represents environmental performance score of firms, *GHG INT* is the greenhouse gas emission scaled by net sales, *TEMP* is defined as the yearly average temperature in ^{0}C, *SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity, *OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. *TEMP* × *GHG INT, TEMP* × *ENV SCORE*, and *GHG INT* × *ENV SCORE* show the interaction between physical risk and climate risk, physical risk and transition risk, climate risk respectively. All continuous variables are winsorized at the 1st and 99th percentile.

	(1)	(2)	(3)
GHG INT	0.997***		1.938***
	(3.699)		(2.677)
TEMP × *GHG INT*	0.882***		
	(5.690)		
TEMP	0.142**	0.142**	
	(2.710)	(2.710)	
TEMP × *ENV SCORE*		0.280***	
		(4.878)	
ENV SCORE		0.638***	0.668**
		(3.975)	(2.372)
GHG INT × *ENV SCORE*			0.732***
			(6.049)
SIZE	0.759**	0.036***	0.076***
	(2.181)	(8.231)	(6.303)
MTB	-0.925***	-0.706*	-0.161***
	(-2.821)	(-1.914)	(-3.273)
LEV	0.202***	0.436	0.166
	(4.479)	(1.272)	(0.633)
OCF	-0.406***	0.631	-0.142***
	(-3.192)	(0.036)	(-5.751)
ROA	-0.262	-0.952	-0.389
	(-0.169)	(-0.517)	(-0.475)
PPE	0.492*	0.002**	0.232***
	(1.914)	(2.903)	(4.442)
CASH	-0.640	-0.599	-0.879
	(-0.612)	(-0.701)	(-1.414)
Constant	0.456	-1.248***	-1.978***
	(1.315)	(-3.817)	(-18.543)
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1,181	1,116	1,193
Adj. R²	0.432	0.592	0.269

Table 6: **Role of probability of default (*PD*)**

CoVaR is the dependent variable, *GHG INT* is the greenhouse gas emission scaled by net sales, *SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity, *OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. Continuous variables are winsorized at the 1st and 99th percentile.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	1M	3M	6M	1Y	3Y	5Y	CoVaR
PD							0.019***
							(3.772)
GHG INT	0.001***	0.001**	0.001***	0.001***	0.001**	0.001**	
	(9.564)	(2.059)	(2.927)	(3.200)	(2.887)	(2.194)	
SIZE	-0.001***	-0.002***	-0.002***	-0.004***	-0.001	-0.002	0.001***
	(-3.836)	(-5.537)	(-2.628)	(-4.246)	(-0.251)	(-0.453)	(15.727)
MTB	0.001	0.001**	0.001	0.001	-0.001	-0.001	0.000***
	(0.008)	(2.054)	(0.205)	(1.265)	(-0.297)	(-0.117)	(4.993)
ROA	0.009*	0.002*	0.018	0.033***	0.038	0.003***	-0.001
	(1.860)	(1.933)	(1.224)	(5.618)	(1.424)	(4.918)	(-1.462)
LEV	0.001**	-0.001	0.001**	0.001	-0.001	-0.001	-0.000**
	(2.499)	(-0.894)	(2.305)	(0.652)	(-0.817)	(-0.705)	(-2.038)
OCF	0.003***	0.002	0.007**	-0.002***	-0.002	-0.012	0.000
	(2.994)	(1.494)	(2.564)	(-4.994)	(-0.161)	(-0.709)	(0.507)
PPE	0.001**	-0.000	0.004***	0.001*	0.012*	0.009	-0.000
	(2.354)	(-1.591)	(2.804)	(1.849)	(1.816)	(1.291)	(-1.547)
CASH	-0.013**	-0.045**	-0.029	0.014	-0.034	-0.020	0.010***
	(-2.269)	(-2.049)	(-1.599)	(0.798)	(-1.108)	(-0.728)	(5.579)
Constant	0.000	-0.064***	-0.016	0.042***	-0.057	0.001	-0.063***
	(0.016)	(-96.731)	(-0.802)	(6.027)	(-0.728)	(0.009)	(-10.075)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	794	794	794	794	794	794	794
Adj. R^2	0.252	0.242	0.346	0.389	0.478	0.629	0.429

Table 7: **Firm heterogeneity by firm size and leverage**

CoVaR is the dependent variable, defined as operating profit before interest and taxes scaled by book value of total assets, *ENV SCORE* represents environmental performance score of firms, *GHG INT* is the greenhouse gas emission scaled by net sales, *TEMP* is defined as the yearly average temperature in ^{0}C, *SIZE* is defined as the natural logarithmic of total assets, *LEV* is defined as ratio of debt to equity, *SGROWTH* is the growth rate of net sales, *OCF* is cash flow from operating activities scales by total assets, PPE is defined as gross property, plant, and equipment scaled by total assets, *INTANG* is the ratio of intangible assets and total assets, *CASH* is firms cash holding scaled by total assets. Continuous variables are winsorized at the 1st and 99th percentile.

	(1) Large firms	(2) Large firms	(3) Large firms	(4) Small firms	(5) Small firms	(6) Small firms	(7) High leverage	(8) High leverage	(9) High leverage	(10) Low leverage	(11) Low leverage	(12) Low leverage
GHG INT	0.030***			-0.011***			0.078***			-0.002*		
	(22.480)			(-10.201)			(11.846)			(-1.970)		
TEMP		0.002***			-0.001***			0.002**			-0.003*	
		(5.148)			(-6.780)			(4.845)			(-2.454)	
ENV SCORE			0.021***			-0.009***			0.019**			-0.010**
			(4.584)			(-3.979)			(2.998)			(-3.498)
SIZE	0.002	-0.025***	-0.233***	-0.023***	-0.027***	0.036	0.003	0.023***	0.013***	-1.712***	-0.005	-0.045
	(0.121)	(-4.015)	(-10.522)	(-4.798)	(-6.404)	(1.216)	(0.421)	(4.137)	(2.873)	(-18.091)	(0.716)	(0.128)
MTB	-0.005***	-0.001***	-0.001***	-0.001**	-0.001***	-0.001	-0.001***	-0.001*	-0.001***	0.005	0.020	-0.168***
	(-6.320)	(-3.040)	(-3.140)	(-2.957)	(-2.991)	(-0.345)	(-5.170)	(3.170)	(-4.043)	(1.471)	(1.407)	(-9.713)
LEV	0.232***	0.237***	0.452***	0.019	0.124***	0.421***	0.222***	0.125***	0.110***	-0.021*	0.004	0.094***
	(6.337)	(6.045)	(4.948)	(0.559)	(5.559)	(3.355)	(6.738)	(5.822)	(7.184)	(-1.900)	(0.559)	(2.673)
OCF	-0.128***	0.036	-0.346***	-0.938***	-0.124**	-1.032***	-0.129***	-0.055**	-0.096***	0.048*	0.022	0.997***
	(-3.048)	(1.523)	(-5.167)	(-4.073)	(-2.378)	(-8.962)	(-2.745)	(-2.725)	(-5.881)	(1.870)	(1.367)	(9.274)
ROA	-0.009	-0.009*	0.049***	-0.055***	0.001	0.093***	-0.003	-0.007*	-0.002	-0.079***	-0.034	-0.677***
	(-0.813)	(-1.405)	(3.813)	(-4.511)	(0.140)	(4.987)	(-0.410)	(-1.904)	(-0.667)	(-5.895)	(-1.138)	(-5.498)
PPE	-0.012	0.074	0.054	0.053**	-0.014	-0.022	-0.020	-0.056	-0.046	0.002	-0.014**	0.088***
	(-0.976)	(0.815)	(0.688)	(2.446)	(-0.296)	(-0.445)	(0.373)	(-1.747)	(-1.571)	(0.735)	(-2.073)	(5.135)
CASH	1.302	-0.020*	0.114	-0.123***	0.095	-0.123***	1.842	0.134	0.100	-0.003	-0.102**	-0.196
	(0.925)	(-2.032)	(0.146)	(-3.751)	(0.385)	(-3.751)	(1.477)	(1.187)	(1.032)	(-0.208)	(-2.765)	(-1.394)
Constant	1.913***	0.064	1.696***	-0.234	-0.266**	1.689***	0.132	-0.042	-0.069*	0.704***	1.060***	2.216**
	(9.204)	(0.435)	(7.158)	(-0.993)	(-1.993)	(9.810)	(0.890)	(-0.748)	(-1.692)	(4.838)	(22.058)	(2.168)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,007	1,800	1,607	1,607	690	5,968	900	1,167	1,607	826	6,574	5,116
Adj. R^2	0.637	0.560	0.637	0.437	0.486	0.438	0.560	0.861	0.644	0.347	0.535	0.392

Table 8: **Green and brown firms and commitment to reduce carbon footprint.**

CoVaR is the dependent variable, *CRISK* is the climate adjusted systemic risk. *ENV SCORE* represents environmental performance score of firms, *TEMP* is defined as the yearly average temperature in ^{0}C, *PHASEOUT* is a dummy variable one for firms commitment to reduce carbon footprint else zero, *SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity, *OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. All continuous variables are winsorized at the 1st and 99th percentile.

	(1) Brown firms	(2) Brown firms	(3) Green firms	(4) Green firms	(5) CoVaR	(6) CRISK
ENV SCORE	0.002**			-0.001**		
	(2.534)			(-2.117)		
TEMP		0.002***	-0.002***			
		(2.980)	(-2.678)			
PHASEOUT					-0.006**	-0.019**
					(-2.059)	(-2.438)
SIZE	0.003***	0.003**	0.003**	0.002***	0.001**	0.109***
	(8.274)	(2.547)	(2.547)	(7.848)	(2.506)	(6.405)
MTB	-0.001	-0.001	-0.001	-0.001**	0.001	-0.711***
	(-1.044)	(-0.457)	(-0.457)	(-2.453)	(1.365)	(-3.452)
LEV	-0.001	-0.002***	-0.002***	0.000	-0.000	-0.242***
	(-0.115)	(-3.231)	(-3.231)	(0.581)	(-0.430)	(-4.047)
OCF	0.001**	-0.015**	-0.015**	-0.002**	-0.001***	-0.043
	(3.070)	(-2.448)	(-2.448)	(-3.073)	(-2.713)	(-0.731)
ROA	-0.001	0.011	0.011	-0.000	0.020***	-0.835**
	(-0.941)	(1.270)	(1.270)	(-0.533)	(4.500)	(-2.325)
PPE	0.001	-0.001	-0.001	0.001	0.001*	0.232***
	(0.820)	(-0.030)	(-0.030)	(1.049)	(1.852)	(5.281)
CASH	-0.115***	0.847***	0.847***	0.029***	-0.064	0.297
	(-2.821)	(2.721)	(2.721)	(8.713)	(-0.456)	(0.250)
Constant	-0.078***	-0.068***	-0.070***	-0.075***	-0.071***	-0.697***
	(-24.647)	(-7.512)	(-7.722)	(-27.781)	(-15.661)	(-6.955)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	923	803	803	923	1,210	1,034
Adj. R^2	0.514	0.576	0.576	0.527	0.370	0.335

Table 9: **Role of corporate default swap (*CDS*)**

CoVaR is the dependent variable, *GHG INT* is the greenhouse gas emission scaled by net sales, *SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity, *OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. Continuous variables are winsorized at the 1st and 99th percentile.

	(1)	(2)	(3)	(4)	(5)	(6)
	1Y	2Y	3Y	4Y	5Y	CoVaR
CDS_1Y						0.001***
						(3.853)
GHG INT	0.050***	0.052***	0.052***	0.051***	0.049***	
	(3.238)	(3.326)	(3.429)	(3.534)	(3.641)	
SIZE	-1.754***	-0.850***	-0.885***	-0.441***	-0.854***	0.001***
	(-4.029)	(-3.934)	(-3.830)	(-3.724)	(-3.610)	(14.914)
MTB	-1.111	-1.294	-1.405	-1.472	-1.519	0.000***
	(-0.944)	(-1.057)	(-1.147)	(-1.220)	(-1.283)	(4.921)
ROA	1.444	0.562	0.739	0.699	0.759	-0.001
	(0.327)	(0.422)	(0.503)	(0.565)	(0.613)	(-1.574)
LEV	15.778*	16.301*	16.260*	16.017*	15.748*	-0.000**
	(1.756)	(1.771)	(1.773)	(1.772)	(1.769)	(-2.156)
OCF	-9.233	-9.813	-9.885	-9.722	-9.479	0.001
	(-1.544)	(-1.583)	(-1.607)	(-1.621)	(-1.627)	(0.693)
CASH	-5.724	-1.233*	-0.032*	-0.252*	-0.458**	-0.001*
	(-1.607)	(-1.739)	(-1.849)	(-1.938)	(-2.014)	(-1.806)
Constant	8.828***	7.083***	4.502***	2.030***	1.554***	0.010***
	(5.307)	(5.343)	(5.345)	(5.331)	(5.307)	(5.917)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,210	1,210	1,210	1,210	1,210	1.210
Adj. R^2	0.414	0.418	0.424	0.431	0.438	0.178

Table 10: **Climate related scenario, and internal carbon pricing (*ICP*)**

For Column (1) and (3) *CRISK* is the dependent variable defined as climate adjusted systemic risk, Column (2) and (4) *CoVaR* is dependent variable*, ICP* is dummy variable, has value of one if firm has internal carbon pricing else zero*, CRS* is dummy variable, has value of one if firm has conducted climate related scenario analysis else zero*, SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity*, OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. All continuous variables are winsorized at the 1st and 99th percentile.

	(1)	(2)	(3)	(4)
	CRISK	CoVaR	CRISK	CoVaR
ICP	-4.684**	-0.003**		
	(-3.081)	(-3.152)		
CRS			-0.686**	-0.002**
			(-3.730)	(-2.966)
SIZE	0.821***	0.003***	0.886***	0.002**
	(2.819)	(6.426)	(3.012)	(2.027)
MTB	-1.816	-0.001	-0.791**	-0.000**
	(-1.301)	(-0.247)	(-2.414)	(-2.218)
LEV	0.161**	-0.000***	-0.784***	-0.000
	(3.219)	(-2.619)	(-16.445)	(-0.285)
OCF	-0.069	0.007	-0.939	-0.000
	(-0.557)	(1.309)	(-0.696)	(-1.276)
ROA	0.648*	0.011**	0.051	0.006**
	(2.025)	(2.095)	(0.177)	(3.429)
PPE	0.219***	-0.000	0.892**	0.001
	(2.948)	(-0.149)	(2.302)	(1.570)
CASH	-0.884	-0.171***	-0.703**	0.002
	(-0.874)	(-7.543)	(-2.124)	(0.139)
Constant	-0.507***	-0.076***	-0.458**	-0.027**
	(-3.312)	(-19.241)	(-2.518)	(-2.207)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	1,216	1,216	1,585	1,585
Adj. R^2	0.594	0.494	0.399	0.322

Table 11: **Robustness test**

For Column (1) (2) and (7) *CRISK* is the dependent variable, defined as climate adjusted systemic risk, Column (3) to (6) *DCoVaR* is dependent variable *ENV SCORE* represents environmental performance score of firms*, TEMP* is defined as the yearly average temperature in ^{0}C, *GHG INT* is the emission intensity derived from greenhouse gas emission*, SIZE* is defined as the natural logarithmic of total assets, *MTB* is the market to book ratio, *ROA* is defined as operating profit before interest and taxes scaled by book value of total assets. *LEV* is defined as ratio of debt to equity*, OCF* is cash flow from operating activities scales by book value of total assets, *PPE* is defined as gross property, plant, and equipment scaled by total assets, *CASH* is firms cash holding scaled by total assets. All continuous variables are winsorized at the 1st and 99th percentile.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	CRISK	CRISK	DCoVaR	DCoVaR	DCoVaR	DCoVaR	CRISK
GHG INT	1.894***		0.001***				
	(4.448)		(3.077)				
ENV SCORE		9.514***		0.001**			
		(3.363)		(2.059)			
TEMP					0.001*		
					(1.703)		
SPEI						-0.001*	-0.475***
						(-1.792)	(-3.677)
SIZE	0.908***	5.500***	0.003***	0.002***	0.001***	0.002***	0.001***
	(9.126)	(6.258)	(6.000)	(15.537)	(12.322)	(10.472)	(11.996)
MTB	1.758	-1.617***	0.001*	0.001**	0.001***	0.000***	0.459
	(0.578)	(-3.841)	(1.969)	(2.054)	(3.811)	(3.273)	(0.825)
ROA	1.341***	6.370	-0.001	-0.001	-0.001	0.002*	-0.033**
	(6.995)	(0.444)	(-0.293)	(-1.591)	(-1.231)	(1.694)	(-0.269)
LEV	-1.610*	1.229***	0.001	-0.001	-0.000***	-0.000	-0.714
	(-1.770)	(2.788)	(0.223)	(-0.894)	(-3.257)	(-1.416)	(-0.703)
OCF	0.006	0.655	-0.000	0.002	-0.001	0.002**	0.923**
	(0.525)	(0.331)	(-0.684)	(1.494)	(-0.617)	(2.015)	(2.494)
PPE	0.120	-75.449	-0.022	-0.045**	0.015	-0.000	0.293*
	(1.091)	(-0.196)	(-1.004)	(-2.049)	(0.652)	(-0.645)	(1.720)
CASH	0.174	-0.293*	-0.974***	-0.002*	0.001	-0.039*	0.709
	(0.039)	(-1.890)	(-8.484)	(-1.833)	(0.568)	(-1.685)	(0.038)
Constant	-0.328***	-1.443***	-0.074***	-0.064***	-0.063***	-0.064***	-0.247***
	(-6.250)	(-5.863)	(-18.484)	(-6.731)	(-6.139)	(-18.050)	(-10.385)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,702	6,340	1,702	4,340	3,803	3,803	3,803
Adj. R^2	0.387	0.578	0.502	0.242	0.253	0.224	0.327

Appendix 1: Variable definition

Variable	Description
CoVaR	Conditional value at risk
CRISK	Climate adjusted systemic risk
CRI SCORE	Climate risk index published by Germanwatch
TEMP	Average of monthly maximum and minimum temperature exposure of firm over a year
PERCP	Pecipitation exposure of the firms
ENV SCORE	Reflects the environmental performance, carbon emission, energy efficiency policy of the firm.
GOV SCORE	Reflects a company's ability to manage and control its operations effectively through best management practices
SOC SCORE	Reflect the social performance and commitment of the firm to the community
ESG SCORE	It measures a firm performance in three key areas: environmental, social, and governance
CTAX	₹400 per tonne of coal (carbon emission)
SIZE	Natural logarithm of the market value of equity
MTB	Price to book ratio
ROA	Earnings before interest and taxes scaled by book value of total assets
SGROWTH	Growth rate of net sales
LEV	Ratio of total debt to total assets
PPE	Property, plant and equipment scaled by total assets
OCF	Cash flow from operating activities scales by book value of total assets
CASH	Cash holding of firms scaled by book value of total assets
EN	Index for el-nino
ϑ_j	Industry fixed effect
δ_T	Year fixed effect