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Climate change and corporate credit worthiness: International evidence

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ABSTRACT

This study examines how climate change risks affect corporate credit ratings worldwide. Using a comprehensive dataset of 4427 firms across 60 countries, we find that firms in countries more susceptible to climate change receive lower credit ratings. Such a negative relation ensues from inferior firm fundamentals, such as higher default risk and cash flow volatility associated with climate-change-related uncertainties. We also find that the adverse impact of climate change risks on credit ratings impedes firms' access to debt financing and increases the costs of holding credit default swaps. Further analyses reveal that institutional factors and market attention to climate change significantly shape rating agencies' responses to climate change risks.

1. Introduction

Over the past decades, the world economy has witnessed notable economic losses due to climate change and climate-related disasters (e.g., Barrot & Sauvagnat, 2016; Lesk, Rowhani, & Ramankutty, 2016; Nordhaus, 2019). Given the rising concerns about climate challenges, financial market participants have considered the implications of climate change on their financing decisions (e.g., Bolton & Kacperczyk, 2021; Chavaz, 2016; Engle, Giglio, Kelly, Lee, & Stroebel, 2020; Massa & Zhang, 2021). Since credit ratings are among the primary indicators of credit risk (Kisgen, 2007; Kuang & Qin, 2013; Standard and Poor's, 2002) and a critical concern of debtholders (Graham & Harvey, 2001), this study seeks to understand the effects of climate change risks on firms' credit ratings and their economic implications to the financial markets worldwide.

Credit rating agencies (CRAs *hereafter*) have recently paid closer attention to non-financial risks when constructing their ratings. Major CRAs have acquired entities with in-house environmental knowledge as a cue for considering environmental risks in their ratings. For instance, S&P purchased Trucost, a leader in carbon and environmental data and risk analysis, in 2016, while Moody's bought Four Twenty-Seven, a provider of market intelligence on climate change risks, in 2019. These moves underscore the CRAs' rising concerns about environmental factors, particularly climate change, in the constitution of their ratings. While anecdotal evidence

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implies the relevance of climate change as a (downside) risk factor for credit rating,[1] empirical evidence remains relatively scant concerning how climate change risks are associated with firm-level credit assessments.[2] Our study fills this gap in the literature and questions how CRAs factor climate change risks when evaluating a firm's credit risk in a cross-country setting.

This question is pertinent for two main reasons. First, while rating agencies admit that environmental risks are a critical attribute of their default risk assessment,[3] it is unclear whether and how these risks systematically enter their ratings. Incorporating climate change risks is not a universal norm or a routine practice of the global rating industry, given different levels of awareness and concern about climate change and the divergence of interests among CRAs in geographical regions. Second, analyzing the role of climate change, especially in credit risk assessment, is not always straightforward since its effects could be multi-dimensional. To be specific, climate change risks can arise from physical risks (changes in the climate) and different transitional risks, including, but not limited to, regulatory risks (changes in regulations) and technological risks (climate-related technological disruption) (Krueger, Sautner, & Starks, 2020). Each type of risk can simultaneously present challenges and opportunities for businesses. For instance, technological risks can lead companies to reassess their business models and exploit climate change as an opportunity to differentiate their product portfolios and increase firm value. Thus, the impact of climate change risks on corporate default risk and credit assessment is an important yet comprehensively unanswered question.

We use a large sample of 4427 firms across 60 countries from 1997 to 2019 to investigate whether climate change vulnerability affects credit ratings. We obtain data on climate change vulnerability from the Notre Dame Global Adaptation Initiative (ND-GAIN hereafter), which employs 36 core indicators to assess a country's susceptibility to climate hazards. One advantage of the climate change vulnerability measure from ND-GAIN is comprehensiveness, as it considers several different climate change exposure components and includes both acute (event-driven) and chronic (long-term) risks. Our explanatory variable is the vulnerability index from ND-GAIN (denoted *Vulnerability*), which measures a country's current predisposition to climate disruptions. The baseline regressions of *Vulnerability* on credit rating proxies suggest that firms in countries facing higher climate change risks receive lower credit ratings. The negative relation between *Vulnerability* and ratings persists across different model specifications and is economically significant. An interquartile-range increase in the climate change vulnerability index reduces the probability of receiving an investment-grade rating by 0.024, corresponding to a 6.37 % decrease relative to its sample mean.

We adopt two identification strategies to address potential endogeneity issues due to omitted-variable problems in our baseline findings: (i) the difference-in-differences approach (DiD) and (ii) the instrumental variable (IV) estimator. First, we employ two severe climate disasters, namely the 2003 European Heatwave and the 2005 Katrina Hurricane, as exogenous shocks to examine the association between climate change vulnerability and credit ratings. Our DiD regressions show that climate disasters exacerbate the adverse effects of climate change risks on credit ratings, which is consistent with a causal effect of climate change vulnerability on credit ratings.

Second, we instrument the climate change vulnerability index using country-level annual death toll due to climatic events and the proportion of energy consumption generated from renewable sources. The estimated coefficients of the instrumented vulnerability index confirm that climate change vulnerability is negatively and significantly associated with credit ratings. In addition, we perform a battery of robustness tests to ensure that our results are not sensitive to alternative samples and various measures of climate change risks and credit ratings. We also control for the unobservable country- or firm-specific but time-invariant factors in different fixed-effect specifications. All robustness tests speak to the notion that climate change risks impair a firm's credit ratings.

We investigate the underlying mechanisms through which climate change adversely impacts a firm's credit ratings. We find that firms more exposed to climate challenges are subject to greater default risk and experience increased cash flow and earnings volatility. This evidence suggests that CRAs consider climate change vulnerability in their ratings when observing its adverse impact on firms' fundamentals. Our analysis then zooms in on the implications of the relationship between climate change vulnerability and credit ratings on the debt market. Building on the premise that credit ratings effectively reflect a firm's default risk, we ask whether the negative impact of climate change vulnerability on the ratings is conducive to changes in debtholders' perception of firm viability and, thus, the higher cost of debt financing. Our additional tests reveal that climate change vulnerability significantly increases both interests charged on a firm's bank loans and credit default swaps (CDS) spreads. Moreover, we note that holding more cash and reducing the dividend pay-out ratio can help companies to mitigate limited access to debt financing due to the impacts of climate change vulnerability on their credit ratings.

The granular nature of our international sample allows us to draw further insights into the heterogeneous effects of climate change vulnerability on credit ratings based on country-level institutions. We show that firms operating in pro-creditor and environmentally innovative countries are less likely to be downgraded because of climate change vulnerability. In contrast, firms in countries with greater government commitment to resolving climate change issues are more likely to receive lower ratings. This result is consistent with Seltzer, Starks, and Zhu (2022), who document that the regulatory risks associated with climate change can adversely affect bonds' credit ratings. In addition, we document that firms in countries where CRAs have offices tend to experience lower ratings, suggesting that direct exposure to climate change can prompt CRAs to weigh more about climate change risks in their credit

[1] For example, Fitch implemented a trial to incorporate their in-house climate change vulnerability score (Climate.VS) in their rating model (Fitch Ratings, 2023).

[2] Safiullah, Kabir, and Miah (2021) document a negative effect of carbon emissions on a firm's credit ratings. However, this paper only focuses on a single aspect of climate change (e.g., carbon emission) and in a single market setting (e.g., the U.S.).

[3] S&P stated that environmental impacts is one of the factors that "have always played a prominent role in creditworthiness and, thus, in our credit ratings". The report is available at https://www.spglobal.com/ratings/en/special-reports/esg-in-credit-ratings (retrieved on August 9, 2022).

assessment. These cross-sectional findings indicate that, while CRAs generally reckon climate change a downside risk to most firms, they do not uniformly incorporate this type of risk in their assessment of creditworthiness across diverse institutional attributes.

Finally, we examine whether the impact of climate change vulnerability on credit ratings varies with the market interest in climate change after the outcomes of major international climate change conferences. Our subsample analysis shows that following the ratification of the 1997 Kyoto Protocol, there exists a negative and significant relationship between climate change vulnerability and credit ratings. This negative relation became less pronounced after the 2012 United Nations Climate Change Conference failed. However, it resurfaces following the success of the 2015 Paris Agreement.

Our study contributes to the literature in three ways. First, it corroborates the existing research on the effects of climate-related risks on financial markets and corporate outcomes, such as financing costs and credit risk (Alok, Kumar, & Wermers, 2020; Chava, 2014; Engle et al., 2020; Huynh & Xia, 2021; Krueger et al., 2020). While these studies often focus on specific industries or countries, our research provides a more systematic analysis of how climate change risk is priced by debt market participants in a cross-nation setting, recognizing the global nature of this type of risk. By doing so, we also contribute to related international studies on the relationship between climate change and sovereign credit ratings (e.g., Agarwala, Burke, Klusak, Kraemer, & Mohaddes, 2022; Cevik & Jalles, 2023). Yet, rather than looking at sovereign ratings that are largely driven by macro or institutional factors, we delve into the pricing of climate change risk through the lens of firm credit ratings, which are the outcomes of an intricate interplay between both macro conditions and firm-specific variables.

Second, our study offers new insights into the common understanding of how qualitative factors enter credit assessments (e.g., Bonsall IV, Holzman, & Miller, 2017; Cornaggia, Krishnan, & Wang, 2017; Ma, Ruan, Wang, & Zhang, 2021; Pham, Merkoulova, & Veld, 2023). While much of the extant literature examines this topic in the U.S. and several developed markets, research on global credit assessment within diverse institutional environments receives far less attention (e.g., Attig, Driss, & El Ghoul, 2020; Driss, Drobetz, El Ghoul, & Guedhami, 2021; Hung, Kraft, Wang, & Yu, 2022). Our study underscores the existence of a cross-country heterogeneity in the manner that CRAs account for environmental threats, such as climate change, in their evaluation of corporate creditworthiness. Thus, a country's policymakers can utilize our findings to inform their decisions on the timing and implementation of environmental regulations or to strengthen specific institutional factors as a means to alleviate the unfavorable impact of climate-related risks on the private sector.

Third, we add to existing studies on the responses of market participants, such as investors (Bolton & Kacperczyk, 2021), banks (Brown, Gustafson, & Ivanov, 2021; Chavaz, 2016; Cortés & Strahan, 2017; Schüwer, Lambert, & Noth, 2019), and insurance firms (Massa & Zhang, 2021) to climate change risks. Our findings have strategic implications for both firms and investors. In particular, firms may benefit from implementing proactive measures to counteract the negative impact of climate change risks on their credit ratings, such as adjusting their cash holding and payout policies. Investors, on the other hand, may consider revising their investment portfolios in response to the informational changes in the debt market as CRAs amend their credit assessments for climate change risks.

The remainder of this paper is organized as follows. Section 2 provides a review of related literature and empirical predictions. We present our sample and research design in Section 3 and the empirical results in Section 4. Section 5 provides additional analyses, and Section 6 concludes the paper.

2. Related literature and empirical prediction

Credit ratings convey essential credit information that is relevant to investment decisions (Avramov, Chordia, Jostova, & Philipov, 2007; Hand, Holthausen, & Leftwich, 1992), corporate financing (Faulkender & Petersen, 2006), and financial regulation and contracting (Frost, 2007). Given their relevance, the quality of credit ratings continues to spark the public's interest, especially following the 2007–2009 financial crisis when CRAs were criticized for worsening the economic turmoil by not promptly incorporating relevant risk factors into their ratings (see, e.g., Xia, 2014).

CRAs assign ratings based on assessing the likelihood of a company repaying its debt. Traditionally, CRAs consider financial indicators such as profitability, leverage, cash flow adequacy, liquidity, and financial flexibility in their rating assessments.[4] However, there has been growing attention to the importance of non-financial and qualitative factors in the credit risk assessment of CRAs (Bonsall IV et al., 2017; Grunert, Norden, & Weber, 2005; Liberti & Petersen, 2019; Pham et al., 2023). These factors concern how CRAs consider climate change risks in constructing their ratings.

The relationship between climate change risks and credit rating remains unclear, and several predictions exist. On the one hand, climate change risks can negatively affect corporate credit ratings as they create additional uncertainty and negatively impact firm performance. Climate change is expected to amplify the frequency and intensity of weather events, including both chronic and acute occurrences such as hurricanes and droughts. These extreme weather conditions can disrupt business operations and supply chains, leading to lower asset values and higher operating costs, directly impacting a company's cash flows and profitability.[5] Additionally, climate change can create transitional risks, such as regulation and technological changes resulting from new treaties or protocols on

[4] See, for example, the disclosure of S&P rating methodology, assessed from: https://disclosure.spglobal.com/ratings/en/regulatory/article/-/view/type/HTML/id/2570533 (retrieved on October 30, 2021)

[5] In their simulation, Trucost shows that under a moderate climate change scenario in 2050, assets of almost 60 % of companies in the S&P 500 and more than 40 % of companies in the S&P Global 1200 will be at a high risk of physical climate change. Trucost's report is available at: https://www.spglobal.com/en/research-insights/understanding-climate-risk-at-the-asset-level-the-interplay-of-transition-and-physical-risks (retrieved on May 30, 2022)

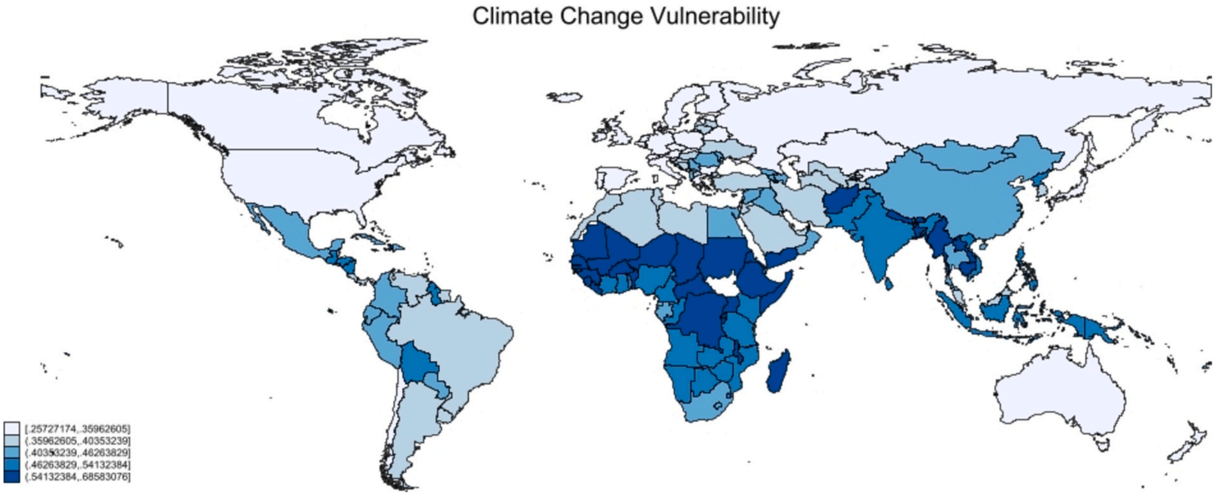

Fig. 1. The figure depicts the average value of the climate change vulnerability index (*Vulnerability*) across 60 countries in our sample from 1997 to 2019. The data is sourced from the Notre Dame Global Adaptation Initiative (ND-GAIN).

climate change, leading to additional costs, demand shifts, and potential liability. The negative impact of climate change risks on a firm's performance can deteriorate its fundamentals and ability to meet financial obligations, negatively affecting its credibility.

On the other hand, firms could also benefit from transition opportunities due to changes in environmental policy and society's perception. Toward the transition into a low-carbon economy, companies can benefit from improved resource efficiency by reducing energy, water, and waste. For example, firms that adopt energy-efficiency measures and develop low-carbon footprint products and services may gain competitive advantages and capitalize on shifting consumer and producer preferences.[6] The use of renewable energy can be a cheaper alternative to scarce fossil energy, thereby helping organizations with cost savings.

As climate change can bring risks and opportunities to firms, it is unclear whether it is priced positively or negatively in credit ratings. In their 2017 report, Standard and Poor's ran a lookback analysis on the outcomes of climate or environmental factors on their rating actions. They found that 44 % of the outcomes are in a positive direction, and 56 % are in a negative direction.[7] Therefore, the sign of environmental risks' effects on firm credit ratings is still inconclusive.

In addition, the interplay of transitional and physical risks creates more difficulty in predicting the effect of climate risk on credit ratings. Companies that take firm actions to limit climate change can reduce the possibility of natural disasters and their physical impacts on their business. However, it would also mean a significant amount expended on limiting emissions (such as technology changes), increasing their transitional risks. Conversely, inaction to adequately reduce emissions may save firms in the short run and reduce transitional risks but will increase climate change exposure and associated physical risks in the future. The interplay of transitional and physical risks could counterbalance the overall impact of climate change risks, leaving no significant effect on credit ratings. In addition, fundamental credit factors such as capital structure, revenue generation ability, and firm liquidity can limit or offset climate change risks. Therefore, from the issuer credit rating perspective, climate change factors may not be material to credit quality.

The relationship between climate risk and credit ratings is not straightforward, as climate change can bring both risks and opportunities to corporations. Therefore, the conflicting predictions urge a comprehensive empirical study, which we discuss in the following sections.

3. Sample and research design

3.1. Data and sample construction

Data on climate change vulnerability comes from the Notre Dame Global Adaptation Initiative (ND-GAIN), which employs 36 core indicators to assess a country's susceptibility to climate hazards. The data covers 182 countries from 1995 to the present and has been widely used by corporations, governments, and NGOs to make informed strategic decisions regarding supply chains, capital projects,

[6] For example, Albemarle Corp is a specialty chemical company based in North Carolina, USA. The company sales grew significantly in 2017 and 2018, due to the increasing demand for lithium batteries - a more environmentally friendly alternative to normal batteries. Its credit rating was also upgraded to BBB from BBB- by Standard and Poor's in 2017. The Standard and Poor's report is available at https://www.spglobal.com/_assets/ratings/research/how-environmental-and-climate-risks-and-opportunities-factor-into-global-corporate-ratings-an-update.pdf (retrieved on October 8, 2022)

[7] See "How Environmental And Climate Risks And Opportunities Factor Into Global Corporate Ratings - An Update", available at:https://www.spglobal.com/en/research-insights/articles/environmental-and-climate-risks-factor-into-ratings (retrieved on October 8, 2022).

policy changes, and community engagements. We also obtain credit rating data from S&P Capital IQ and financial information from the Compustat North America and Global Fundamental annual datasets. Institutional ownership data is from Thomson/Refinitiv's Institutional Holdings (13F) database. Country-level economic and political data is drawn from the World Bank. Other data we employ in this study include bank loan information from the Dealscan database, CDS pricing data from the IHS Markit database, and the number of patents in environment-related technologies from the Organisation for Economic Co-operation and Development (OECD).

Our primary sample intersects the above databases with non-missing values for the fields required for our baseline tests in this paper. Following Kisgen (2006), we exclude financial firms (SIC codes 6000–6900) as these firms are subject to different rating criteria than those used for non-financial firms. After merging all databases, the final sample consists of 16,206 firm-year observations for 4427 unique firms from 60 countries between 1997 and 2019.

3.2. Climate change vulnerability measure

Our explanatory variable of interest is the vulnerability index from ND-GAIN (denoted *Vulnerability*), which measures a country's current predisposition to climate-change-related disruptions. This index is constructed based on six indicators related to the *exposure*, *sensitivity*, and *adaptive capacity* to climate change across six life-supporting sectors of each country: food, water, health, ecosystem services, human habitat, and infrastructure.[8] The vulnerability index from ND-GAIN is forward-looking and captures both short-term and long-term physical and transition risks associated with climage change. A higher value of *Vulnerability* reflects a greater urgency for adaptation action to mitigate the consequences of climate change. Fig. 1 presents the average climate change vulnerability index across countries in our sample.

We also employ alternative climate change vulnerability measures to ensure the robustness of our empirical results. The first measure is the *ND-GAIN Score*, which accounts for a country's vulnerability to climate change and its readiness to cope with climate events. The second measure, the *WSJ Climate Change News Index*, developed by Engle et al. (2020), estimates the intensity of climate change news coverage in the Wall Street Journal.

3.3. Credit rating measure

We follow credit rating literature and adopt a numerical translation of S&P long-term issuer ratings to construct our key dependent variable (denoted *Rating*) (e.g., Ashbaugh-Skaife, Collins, & LaFond, 2006; Bonsall IV et al., 2017; Cornaggia et al., 2017; Kuang & Qin, 2013). We first collect long-term foreign-currency credit ratings at the issuer level from the S&P Capital IQ database. We then assign numbers from 1 to 25, corresponding to the S&P ratings range from D (lowest rating and default on debt) to AAA (highest rating), to conduct our empirical analysis. A higher value of the numerical ratings indicates a lower expected default risk. For each fiscal year, we keep the first rating available immediately after the three-month window following the previous year-end since this gap ensures that our ratings reflect publicly available information (e.g., Driss et al., 2021). We also employ outlook-adjusted numerical ratings (*Adj_Rating*), similar to Driss et al. (2021), for robustness tests. Specifically, *Adj_Rating* is a *Rating* changed by +0.5 for a positive outlook or by −0.5 for a negative outlook; no adjustment is made for a stable, developing, or missing outlook from the data.

3.4. Research design

To explore whether and how climate change vulnerability affects a firm's credit ratings, we follow Baghai, Servaes, and Tamayo (2014) and estimate the following baseline regression model:

$$\text{Credit Rating}_{i,j,t} = \beta_0 + \beta_1 \text{Vulnerability}_{j,t-1} + \sum \gamma_i X_{i,t-1} + \sum \theta_j Z_{j,t-1} + \varepsilon_{i,j,t} \quad (1)$$

where the subscripts *i, j,* and *t* index firms, countries, and years, respectively. *Credit Rating* alternatively denotes our two firm-level rating measures. *Vulnerability* is the one-year lagged ND-GAIN climate change vulnerability index of country *j*.

The vectors of control *X* and *Z* represent extensive sets of the firm- and country-level control variables that are found to affect credit ratings in prior literature. Congruent with prior literature (e.g., Baghai et al., 2014; Driss et al., 2021), we include a range of firm-level controls that can be related to a firm's credit quality, including institutional ownership (*IO*), total debt ratio (*Debt*), debt-to-cash flow ratio (*Debt to* CF), negative debt-to-cash flow ratio dummy (*NegDebt*), interest coverage ratio (*IntCoverage*), firm size (*Size*), operating margin (*OpMargin*) and its volatility (*Std_OpMargin*), rent ratio (*Rent*), asset tangibility (*Tangibility*), and capital expenditures ratio (*CapEx*). Regarding country-specific factors, we control for GDP growth (*GDP*), inflation rate (*Inflation*), and political stability

[8] *Exposure* captures the extent to which human society and its supporting sectors are stressed by future changing climate conditions; *sensitivity* refers to the degree to which people and the sectors they depend upon are affected by climate change related perturbations; and *adaptive capacity* reflects the ability of society and its supporting sectors to adjust to reduce potential damage and to respond to the negative consequences of events related to climate change. For example, *food exposure* is measured by assessing the projected change in food supply due to climate change, comparing cereal yield data from 1980 to 2009 to projections for 2040–2069. The data is then converted into an index using various methods, such as normalizing data to similar ranges, setting base values, scaling data linearly or after transformation, and converting to ranked values, depending on the indicator. For more details on the technical construction of the index, please refer to the ND-GAIN Country Index Technical Report from this link: https://gain.nd.edu/assets/581554/nd_gain_countryindex_technicalreport_2024.pdf.

(*PStability*). We winsorize all continuous variables at the top and bottom 0.5 % to mitigate concerns about outliers. Our baseline specifications include two-digit SIC industry- and year-fixed effects to account for time- and industry-invariant factors associated with credit ratings.[9] We employ robust standard errors corrected for heteroskedasticity and clustered by country and year dimensions to account for dependence across country and time (Cameron, Gelbach, & Miller, 2011; Gow, Ormazabal, & Taylor, 2010; Petersen, 2009).[10] Appendix A presents the definitions of all variables.

3.5. Descriptive statistics

Tables 1 and 2 display the distribution by country and descriptive statistics of our key variables. Table 1 Column (5) reports each country's average value of *Vulnerability*, which falls between 0.2543 (Norway) and 0.490 (India). We also infer from the distribution that countries in Asia or Africa are generally more prone to climate change than those in Europe or America. Similar patterns are observable in alternative climate change risk measures in untabulated results. As shown in Panel A of Table 2, an average firm in our sample has a numerical (adjusted) rating of 14.0, equivalent to a BB-rated entity and comparable with previous studies.

Panel B of Table 2 presents the correlations among all variables. Two findings are noteworthy. First, the correlation between *Vulnerability* and credit ratings is marginally negative, with a coefficient of −0.02. This motivates us to conduct further analysis to understand the nature of such association when controlling for other economic actors in a multivariate setting. Second, while most control variables are significantly associated with rating measures, all pairwise correlation coefficients are below 0.8, with the highest value reported at 0.65 between *OpMargin* and *IntCoverage*, alleviating concerns about multicollinearity problems.

4. Empirical results

4.1. Baseline results

Table 3 reports the estimation results of Eq. (1) to examine the association between climate change vulnerability and a firm's credit ratings using different control variables and fixed effects. In Columns (1) and (2) of the table, we estimate the simple regression model of firm-level credit ratings on climate change vulnerability, while Columns (3) and (4) expand the model with controls for the firm and macroeconomic fundamentals. The results suggest that climate change vulnerability is negatively and significantly associated with firm-level credit ratings at a 1 % level. For instance, the coefficient of *Vulnerability* on *Rating* in Column (1) is −6.975 (p-value <0.01) without including any control variables or fixed effects. The coefficient becomes slightly smaller ($\beta_1 = -5.868$ with p-value <0.01) while remaining statistically significant after accounting for the firm- and country-specific controls along with industry and year-fixed effects in Column (3). The impact of *Vulnerability* persists when *Adj_Rating* serves as an alternative dependent variable in Columns (2) and (4).

Since our credit rating measures convey a company's ordinal and non-negative credit risk assessment, using an OLS estimator could be problematic as it assumes uniform differences among the credit grades. Thus, we follow Cheng and Subramanyam (2008) and Cohn, Liu, & Wardlaw (2022) to confirm the robustness of our baseline findings by re-estimating Eq. (1) with two more unbiased and consistent estimators, including ordered logit model in Columns (5) and (6) and fixed-effects Poisson model in Columns (7) and (8).[11] We continue to observe a negative association between climate change vulnerability and credit ratings, regardless of the estimators in use.

The effects of the control variables are also broadly consistent with those of prior literature. We find that firms with a higher proportion of shares held by institutional investors have higher credit ratings, suggesting that these investors help enhance monitoring to tackle agency problems and information risk (Boone & White, 2015; Driss et al., 2021; Elyasiani, Jia, & Mao, 2010). The signs of other coefficients also imply that less financially leveraged, more economically stable, profitable, and larger firms have higher credit ratings because these firms face lower default risks. Finally, we document that firms in countries with higher inflation rates and are politically unstable are more likely to receive lower credit ratings.

In summary, the baseline regression results support our hypothesis that a country's vulnerability to climate change leads to credit rating downgrades. Given the robust findings across various regression specifications, we only use the results of OLS regression models with industry and year-fixed effects in subsequent analyses.

[9] While firm fixed effects can potentially mitigate omitted variable bias, Breuer and Dehaan (2024) caution that the inclusion of granular or high-dimensional fixed effects may reduce the power of empirical tests if within-fixed effect variation is insufficient to identify a true effect. This is particularly likely when fixed effects absorb a significant portion of the variation in the independent variable. In our case, the *Vulnerability* index is calculated at the country level and exhibits relatively stable values over time within each country (with an average within-country mean and standard deviation of 0.3341 and 0.0094, respectively). Additionally, when regressing this index on firm and year fixed effects, the adjusted R^2 is a substantial 96.51 %. Consequently, incorporating firm fixed effects could significantly diminish the power of our test. Yet, we include firm fixed effects in one of our robustness checks to validate the reliability of our baseline results against the omitted-variable bias.

[10] In Table IA2, we also use clustered standard errors at industry-year and firm-year level. We find the statistical significance of the estimated coefficients in our baseline regressions qualitatively unchanged.

[11] As Bernile, Bhagwat, and Rau (2017) noted, the ordered logit estimation can accommodate the varying distances between adjacent rating categories but is more sensitive to many fixed effects.

Table 1
Descriptive statistics of key variables by countries.

	(1)	(2)	(3)	(4)	(5)
Country	#Firms	Obs	Average Rating	Average Adj_Rating	Average Vulnerability
United Arab Emirates	4	6	15.000	14.667	0.3622
Australia	75	227	15.093	15.029	0.3143
Austria	8	46	17.348	17.326	0.2737
Belgium	8	34	17.088	16.926	0.3290
Bulgaria	2	10	11.000	10.900	0.3416
Bahrain	1	5	14.000	13.900	0.4420
Brazil	60	342	12.942	12.896	0.3957
Canada	246	859	13.532	13.446	0.2920
Switzerland	42	142	16.592	16.577	0.2555
Chile	26	103	14.621	14.534	0.3492
China	75	195	14.918	14.826	0.3957
Colombia	6	22	13.364	13.250	0.4116
Cyprus	2	5	10.600	10.600	0.3495
Czech Republic	3	9	18.000	17.833	0.2800
Germany	75	342	16.295	16.246	0.2892
Denmark	11	44	16.682	16.727	0.3332
Dominican Republic	1	2	10.000	9.500	0.4333
Egypt	1	1	14.000	14.000	0.4556
Spain	35	135	15.474	15.393	0.2939
France	77	374	16.184	16.128	0.2921
United Kingdom	192	632	14.981	14.884	0.2857
Greece	14	58	11.862	11.724	0.3255
Hungary	4	14	15.143	15.214	0.3666
India	22	67	14.343	14.351	0.4897
Ireland	32	98	14.786	14.760	0.2990
Israel	2	9	16.889	16.944	0.3071
Italy	32	152	15.625	15.474	0.3210
Japan	239	594	17.828	17.785	0.3567
Kazakhstan	5	19	14.368	14.263	0.3377
Cambodia	1	2	11.500	11.500	0.4897
Korea, Republic of	28	121	16.810	16.818	0.3761
Sri Lanka	1	4	12.000	11.875	0.4636
Lithuania	1	6	17.167	17.417	0.3746
Luxembourg	26	103	13.427	13.427	0.2913
Morocco	1	2	16.000	16.000	0.3807
Mexico	44	178	12.921	12.882	0.4092
Mongolia	1	5	8.600	8.400	0.3885
Malaysia	10	39	16.667	16.628	0.3699
Nigeria	1	2	10.500	10.500	0.4897
Netherlands	48	191	15.524	15.471	0.3495
Norway	12	62	14.452	14.323	0.2543
New Zealand	21	58	17.379	17.388	0.3111
Oman	1	4	16.500	16.125	0.3933
Peru	10	26	13.615	13.442	0.4421
Philippines	5	29	13.586	13.569	0.4819
Poland	11	38	12.053	12.053	0.3197
Portugal	7	43	17.767	17.709	0.3381
Qatar	1	3	19.333	19.167	0.3618
Romania	2	9	14.667	14.611	0.4052
Russian Federation	57	286	12.815	12.876	0.3459
Saudi Arabia	4	9	19.778	19.611	0.3996
Singapore	15	40	16.675	16.613	0.3921
Slovenia	2	2	15.500	15.250	0.2990
Sweden	36	156	15.814	15.756	0.2839
Thailand	15	43	13.767	13.686	0.4315
Trinidad and Tobago	1	3	9.667	9.667	0.3705
Turkey	9	51	12.804	12.735	0.3586
Ukraine	1	6	9.667	9.500	0.3694
United States	2745	10,092	13.489	13.423	0.3379
South Africa	10	47	14.638	14.383	0.4084
Total	4427	16,206			

4.2. Investment versus speculative-grade analysis

Given that our credit rating measures represent polytomous ordinal risk assessment, the marginal effects of changes in climate change vulnerability on credit ratings are not easy to quantify. To alleviate this concern, we employ an alternative scheme that

Table 2
Summary statistics and Pearson correlation matrix.

Panel A: Summary statistics.

Variable	Obs	Mean	SD	P25	Median	P75
Rating	16,206	14.07	3.95	12.00	14.00	17.00
Adj_Rating	16,206	14.00	3.97	11.50	14.00	17.00
Vulnerability	16,206	0.33	0.03	0.32	0.34	0.35
IO	16,206	0.35	0.37	0.00	0.19	0.73
Debt	16,206	0.27	0.22	0.01	0.27	0.42
Debt to CF	16,206	2.74	5.03	0.00	2.10	4.01
IntCoverage	16,206	11.82	41.98	0.00	3.80	8.19
NegDebt	16,206	0.02	0.15	0.00	0.00	0.00
Size	16,206	6.55	3.96	5.53	7.52	8.93
OpMargin	16,206	0.15	0.18	0.01	0.12	0.23
Rent	16,206	0.01	0.03	0.00	0.00	0.01
Tangibility	16,206	0.31	0.29	0.03	0.24	0.55
CapEx	16,206	0.06	0.09	0.00	0.04	0.07
Std_OpMargin	16,206	0.06	0.21	0.00	0.02	0.04
GDP	16,206	2.62	2.11	1.64	2.59	3.80
Inflation	16,206	2.48	2.44	1.55	2.19	2.93
Pstability	16,206	0.57	0.53	0.35	0.59	0.94

Panel B: Correlation matrix

	Rating	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1) Adj_Rating	0.9964*															
(2) Vulnerability	−0.0202*	−0.0173*														
(3) IO	−0.0270*	−0.0312*	−0.2224*													
(4) Debt	−0.1175*	−0.1188*	−0.0253*	0.1428*												
(5) Debt to CF	−0.0677*	−0.0689*	−0.0406*	0.1285*	0.8152*											
(6) IntCoverage	0.3343*	0.3278*	−0.0479*	0.2693*	0.1997*	0.2272*										
(7) NegDebt	−0.1448*	−0.1424*	0.0074	0.0182*	0.1065*	−0.2612*	−0.2591*									
(8) Size	0.3349*	0.3305*	−0.0224*	0.2049*	0.4684*	0.5178*	0.5834*	−0.0021								
(9) OpMargin	0.2139*	0.2104*	−0.0517*	0.1509*	0.5039*	0.4754*	0.6476*	−0.2591*	0.5662*							
(10) Rent	−0.1139*	−0.1167*	−0.0094	0.3681*	0.3875*	0.3281*	0.3886*	0.0502*	0.2574*	0.2259*						
(11) Tangibility	0.1193*	0.1178*	−0.0170*	0.0607*	0.5785*	0.5184*	0.4590*	0.0672*	0.5809*	0.6610*	0.2478*					
(12) CapEx	0.0965*	0.0939*	0.00	0.1390*	0.4948*	0.4043*	0.5515*	0.0638*	0.5232*	0.5946*	0.3944*	0.7878*				
(13) Std_OpMargin	−0.0689*	−0.0685*	−0.0226*	0.1982*	0.5280*	0.4626*	0.3955*	0.1929*	0.4888*	0.6067*	0.3058*	0.6367*	0.5812*			
(14) GDP	−0.0115	−0.01	0.2136*	−0.2195*	−0.0514*	−0.0748*	−0.0228*	−0.0217*	−0.0898*	0.0042	−0.0197*	0.0019	0.0474*	−0.0158*		
(15) Inflation	−0.1241*	−0.1212*	0.2478*	−0.0371*	−0.0204*	−0.0488*	−0.0593*	−0.0185*	−0.0712*	0.0100	0.0318*	0.0028	0.0261*	0.0251*	0.2142*	
(16) Pstability	0.1399*	0.1398*	−0.1638*	−0.1982*	−0.0348*	−0.0407*	−0.0248*	0.0236*	−0.0639*	−0.0817*	−0.0996*	−0.0117	0.0017	−0.0885*	0.0004	−0.2492*

The table displays summary statistics (Panel A) and Spearman's rank correlation coefficients (Panel B) of the variables we use for our baseline regressions. *Rating* is the numerical translation of long-term foreign-currency credit ratings at the issuer level by S&P. We assign numbers from 1 to 25, corresponding to the S&P ratings range from D (lowest rating and default on debt) to AAA (highest rating) so that a higher value of the numerical ratings indicates a lower expected default risk. *Adj_Rating* is a *Rating* adjusted by +0.5 for a positive outlook or by −0.5 for a negative outlook; no adjustment from the data is made for a stable, developing, or missing outlook. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. Detailed definitions of other firm-level control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. * in our correlation matrix indicates a correlation that is statistically significant at a 5 % level. The sample period is from 1997 to 2019. *Obs* denotes the number of observations.

Table 3
Climate change vulnerability and firm-level credit ratings.

	OLS Estimator				Ordered Logit Estimator		Fixed-effects Poisson	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	Rating	Adj_Rating	Rating	Adj_Rating	Rating	Adj_Rating	Rating	Adj_Rating
Vulnerability	−6.975***	−6.645***	−5.868***	−5.936***	−3.463***	−3.412***	−0.458***	−0.465***
	(0.000)	(0.000)	(0.003)	(0.003)	(0.004)	(0.003)	(0.001)	(0.001)
IO			0.252**	0.253**	0.152**	0.136*	0.027***	0.027***
			(0.033)	(0.035)	(0.032)	(0.055)	(0.002)	(0.002)
Debt			−5.186***	−5.231***	−2.931***	−2.910***	−0.374***	−0.380***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt to CF			−0.113***	−0.113***	−0.067***	−0.065***	−0.009***	−0.009***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IntCoverage			−0.001	−0.001	−0.000	−0.000	−0.000**	−0.000**
			(0.399)	(0.384)	(0.634)	(0.669)	(0.032)	(0.030)
NegDebt			−3.225***	−3.230***	−1.847***	−1.794***	−0.280***	−0.281***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Size			0.410***	0.410***	0.250***	0.246***	0.029***	0.029***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
OpMargin			1.452***	1.412***	0.790***	0.751***	0.122***	0.120***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Rent			−11.648***	−11.787***	−7.089***	−7.064***	−0.919***	−0.937***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility			−0.228	−0.198	−0.149	−0.135	−0.016	−0.014
			(0.286)	(0.350)	(0.184)	(0.217)	(0.297)	(0.362)
Capex			−1.382***	−1.303***	−0.840***	−0.780***	−0.101***	−0.094***
			(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)
Std_OpMargin			−1.295***	−1.279***	−0.786***	−0.758***	−0.121***	−0.120***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP Growth			0.034	0.032	0.020	0.017	0.003	0.003
			(0.265)	(0.302)	(0.243)	(0.318)	(0.190)	(0.221)
Inflation			−0.169***	−0.160***	−0.098***	−0.091***	−0.013***	−0.012***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Pstability			0.667***	0.677***	0.345***	0.352***	0.045***	0.046***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	16,206	16,206	16,206	16,206	16,206	16,206	16,206	16,206
Adj./Pseudo R^2	0.003	0.003	0.333	0.333	0.0823	0.066	0.0665	0.0675
Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes

partitions credit ratings into two groups, investment grade and speculative grade, instead of the numerical translation. Such a dichotomous classification allows us to readily assess the economic impact of climate change vulnerability on firm-level credit ratings.

We introduce a new variable, denoted as *Investment Grade*, a dummy that equals one if a firm's credit rating is BBB- or better and zero otherwise. We then estimate a logistic regression of *Investment Grade* on the climate change vulnerability index and the controls as specified in Eq.(1). Table 4 displays the estimation results of the logistic regressions. Consistent with our baseline findings, we continue to document a negative association between *Vulnerability* and *Investment Grade*, suggesting that a greater level of climate change risk significantly reduces the probability of receiving an investment-grade credit rating. To provide some insight into the economic significance of our results, we follow Ashbaugh-Skaife et al. (2006) and use the changes in the probability of an average firm receiving an investment-grade credit rating when moving from the first (Q1) to the third quartile (Q3) values of *Vulnerability*.

To be specific, we first estimate the probability of achieving an investment-grade credit rating from our logistic regression model using the following expression:

$$\pi(X) = e^{\beta' X} / \left(1 + e^{\beta' X}\right) \tag{2}$$

where β is the vector of estimated coefficients reported in column (1) of Table 4, and X is the vector of explanatory variables set equal to their mean values. Next, we compute the probability, $\pi(X)$, at the lower (Q1) and upper quartile (Q3) values of each explanatory variable while holding the other variables constant at their means. The likelihood of receiving an investment-grade credit rating changes as each independent variable moves from its Q1 to Q3 values are tabled in column (2). For the marginal effects of *Vulnerability,*

Table 4
Economic significance.

	(1)	(2)
Variable	Investment Grade	ΔProbability(Q3 – Q1)
Vulnerability	−5.210***	−0.024
	(0.001)	
IO	−0.022	−0.003
	(0.845)	
Debt	−3.806***	−0.287
	(0.000)	
Debt to CF	−0.133***	−0.098
	(0.000)	
IntCoverage	−0.002***	−0.003
	(0.000)	
NegDebt	−3.693***	0.000
	(0.000)	
Size	0.306***	0.195
	(0.000)	
OpMargin	1.664***	0.066
	(0.000)	
Rent	−12.012***	−0.030
	(0.000)	
Tangibility	−0.130	−0.012
	(0.411)	
CapEx	−1.956***	−0.024
	(0.000)	
Std_OpMargin	−6.423***	−0.046
	(0.000)	
GDP	0.008	0.003
	(0.725)	
Inflation	−0.178***	−0.044
	(0.000)	
Pstability	0.370***	0.039
	(0.002)	
Obs	16,185	
Adj./Pseudo R^2	0.283	
Industry FE	Yes	
Year FE	Yes	

This table presents the logistic regression of the probability of a firm receiving an investment-grade rating on climate change vulnerability in column (1). *Investment grade* is an indicator variable that takes the value of one if a firm's credit rating is BBB- or better each year and zero otherwise. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. Column (2) reports the changes in the probability of receiving an investment-grade credit rating due to moving from the first to the third quartile value of climate change risks, holding all other variables constant at their mean values. Detailed definitions of control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. The sample period is from 1997 to 2019. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

we observe a 0.024 (or 2.40 %) reduction in the likelihood of a firm's receiving an investment-grade credit rating if climate change risks of the country where it is operating increase by one interquartile range [Q3 – Q1], holding other covariates constant at their means. Given that the mean value of *Investment Grade* in our sample is approximately 0.377, this marginal effect of *Vulnerability* translates into a decrease of 6.37 % (=0.024/0.377) relative to its mean, which is comparable to the impact of some firm fundamentals such as *CapEx, Rent*, and *Tangibility*, and is stronger than that of institutional ownership and interest coverage.[12]

4.3. Robustness tests and identification strategies

Our empirical analysis has revealed a negative association between a firm's vulnerability to climate change and its credit rating.

[12] To enhance the interpretability of our empirical findings in terms of economic significance, we present standardized regression coefficients in Table IA1. Our results indicate that a one-standard-deviation increase in the *Vulnerability* is associated with a 0.046-standard-deviation decrease in credit ratings. This effect is stronger compared to some well-established determinants of credit ratings, such as institutional ownership, capital investment, and operating profit volatility. These findings are largely consistent with our inter-quartile analysis.

However, this relationship could be influenced by unobserved firm-specific factors or measurement errors that distort the true impact of climate change risk on creditworthiness. To address these potential confounders, we conducted a series of robustness checks using alternative metrics for vulnerability and credit ratings, different data samples, and modeling approaches, the results of which are presented in Table 5. Additionally, we employed difference-in-differences analysis based on climate disasters and an instrumental variable (IV) estimation technique to mitigate the endogeneity concerns arising from omitted variable bias, as detailed in Tables 6 and 7, respectively.

4.3.1. Robustness tests

In Table 5, Panel A, we employ alternative measures of climate change vulnerability and credit ratings. Columns (1) to (4) present the regression results of *Rating* and *Adj_Rating* on two different proxies for climate change risks: (1) the ND-GAIN country index (*ND-GAIN*), which is estimated by subtracting each country's vulnerability score from its readiness score and is scaled to yield a value between 0 and 100; and (2) Wall Street Journal climate change news index (*WSJ*) developed by Engle et al. (2020), which associates increased climate change reporting with news about elevated climate change risks.[13] Since lower values of *ND-GAIN* (i.e., readiness net of vulnerability) indicate higher climate change risks, we multiply this index by −1 to reconcile their interpretation with *WSJ*. The results reinforce our baseline finding that climate change risks impair a firm's credit ratings.

Scholars have raised concerns that credit ratings provided by major issuer-paid rating agencies could lack timeliness and cater to issuers' interests, compromising the rating quality (Becker & Milbourn, 2011; Cornaggia & Cornaggia, 2013; Xia, 2014). Therefore, growing attention has been given to independent and investor-paid rating providers, e.g., Egan-Jones, that might produce more informative and timely ratings (Beaver, Shakespeare, & Soliman, 2006; Chemmanur, Karagodsky, & Toscano, 2020). To ensure that our main results are not merely a manifestation of issuer-biased ratings, we re-estimate our baseline regressions using Egan-Jones ratings (*EJR*) as the dependent variable of interest. Column (7) of Table 5 Panel A shows a negative and statistically significant coefficient of *Vulnerability* on *EJR*, reinforcing our baseline findings.

Second, the distribution of our sample by country in Table 1 shows that our sample is largely comprised of developed markets, especially the U.S., where credit ratings are more available. To alleviate the concerns that our empirical findings are driven by either firms located in the U.S. or the outlier countries, we, therefore, exclude these firms from our sample and re-estimate the baseline Eq. (1). Columns (1) to (2) of Panel B display the baseline regression estimates using alternative samples of non-U.S. firms and those countries with more than five years of data for at least five firms (25 observations). We draw similar conclusions from these models.

Third, although we have controlled for factors that affect a firm's credit ratings, our specifications might omit unobservable country- or firm-specific characteristics, which remain constant over time. Therefore, we modify our specifications with different sets of fixed effects to resolve these concerns. In Table 5 Panel C, we extend our baseline Eq.(1) with different sets of fixed effects, including country, firm, and industry-year fixed effects. Across these alternative specifications, we observe negative and statistically significant coefficients of *Vulnerability* on credit ratings. The magnitude of these coefficients was either similar or larger than those reported in Table 1, further reinforcing the validity of our baseline findings.[14]

Finally, to account for the influence of changes in country-level institutions on firm credit ratings, we include several institutional variables in Panel D. These variables, obtained from Our World in Data, the World Bank, and the International Monetary Fund (IMF), include real GDP per capita, the rule of law, and financial development. Additionally, we incorporate control for creditors' legal rights against defaulting debtors using the composite creditor rights index (*Creditor Rights*) developed by Djankov, La Porta, Lopez-de-Silanes, and Shleifer (2008), which is based on the original index by La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997).[15] Our empirical findings remain consistent even after controlling for these institutional factors.

4.3.2. Difference-in-differences approach

Our first identification strategy to address the omitted-variable problem uses extreme climate disasters as an experimental platform to examine the association between climate change vulnerability and credit ratings. Climatic disasters are exogenous to a firm's credit ratings and, at the same time, engender an increase in market attention to climate change issues (Li, Lin, & Lin, 2022; Sautner, van Lent, Vilkov, & Zhang, 2023). Thus, we expect that firms in countries hit by these disasters may subsequently experience a decline in their credit ratings. We empirically test our conjecture using the two notable climate disasters of the 21st century, the 2003 European Heatwave and the 2005 Katrina Hurricane, which resulted in significant loss of life and were economically costly. For each event, we estimate the following difference-in-differences (DiD) regression using an event window of two years before and after the event year (i.

[13] Alternatively to those measures of climate change risks, we consider the measure of climate risk and its consequences to credit rating by employing the Germanwatch climate risk index (CRI). This index ranks impact scores of extreme weather events in terms of economic losses and fatalities, and indicates the level of future exposure and vulnerability to extreme events. In untabulated results, we document a negative and significant relation between CRI and credit rating.

[14] We conduct additional analyses in Table IA2 using various clustering approaches. Our results remain statistically significant regardless of the clustering method employed, indicating that the observed effects are not driven by specific assumptions about the correlation structure of the data."

[15] This index ranges from 0 to 4, and one point is added to the index when a country's laws and regulations provide each of the four powers secured lenders have in the event of bankruptcy. These powers include: (1) whether there are restrictions, such as creditor consent when a debtor files for reorganization; (2) whether secured creditors can freely seize their collateral after the petition for reorganization is approved; (3) whether secured creditors are paid first out of the proceeds of firm liquidation; and (4) whether an administrator, not management, is responsible for running the business during the reorganization.

Table 5
Robustness tests.

Panel A: Alternative measures of climate change risks and credit rating

Variable	(1) *Rating*	(2) *Adj_Rating*	(3) *Rating*	(4) *Adj_Rating*	(5) *EJR_Rating*
ND_Gain	−0.1065***	−0.1083***			
	(0.001)	(0.001)			
WSJ Climate Change News Index			−95.258**	−91.738*	
			(0.048)	(0.060)	
Vulnerability					−6.802***
					(0.001)
Obs	16,205	16,205	15,986	15,986	14,342
Adj. R^2	0.378	0.378	0.291	0.290	0.446
Controls	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Panel B: Alternative samples

	Non-U.S. countries		At least five firms over five years	
	(1)	(2)	(3)	(4)
Variable	*Rating*	*Adj_Rating*	*Rating*	*Adj_Rating*
Vulnerability	−27.505***	−28.007***	−5.629***	−5.659***
	(0.001)	(0.001)	(0.006)	(0.006)
Obs	6114	6114	16,088	16,088
Adj. R^2	0.392	0.392	0.334	0.334
Controls	Yes	Yes	Yes	Yes
Country FE	No	No	No	No
Industry FE	Yes	Yes	Yes	Yes
Firm FE	No	No	No	No
Year FE	Yes	Yes	Yes	Yes

Panel C: Different fixed-effects models

	Country FE		*Firm FE*		*Industry × Year FE*	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*Rating*	*Adj_Rating*	*Rating*	*Adj_Rating*	*Rating*	*Adj_Rating*
Vulnerability	−27.505***	−28.007***	−5.629***	−5.659***	−7.575***	−7.656***
	(0.001)	(0.001)	(0.006)	(0.006)	(0.000)	(0.000)
Obs	6114	6114	16,088	16,088	16,206	16,206
Adj. R^2	0.392	0.392	0.334	0.334	0.377	0.377
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	No	No	No	No
Industry FE	Yes	Yes	No	No	Yes	Yes
Firm FE	No	No	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	No	No	No	No	Yes	Yes

Panel D: Additional controls

Variable	(1) *Rating*	(2) *Adj_Rating*
Vulnerability	−5.428**	−5.441**
	(0.017)	(0.017)
Real GDP per capita	0.280	0.310
	(0.217)	(0.173)
Rule of Law	−0.998*	−1.056*
	(0.068)	(0.052)
Financial Development	3.624***	3.679***
	(0.000)	(0.000)

(*continued on next page*)

Table 5 (*continued*)

Panel D: Additional controls		
	(1)	(2)
Variable	*Rating*	*Adj_Rating*
Creditor Rights	0.487***	0.487***
	(0.000)	(0.000)
Obs	16,002	16,002
Adj. R^2	0.356	0.356
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

This table reports the robustness tests for the relationship between climate change risk and credit ratings. These include using alternative measures of climate change risk and credit ratings (Panel A), alternative samples (Panel B), and various model specifications (Panels C & D). *ND_Gain* is the global adaptation index from ND-GAIN that accounts for a country's vulnerability to climate change and its readiness to cope with climate events. *WSJ Climate Change News Index is* the intensity of climate news coverage in the Wall Street Journal developed by Engle et al. (2020). *EJR_Rating* is the numerical translation of issuer-level credit ratings issued by Egan Jones. *Rating* is the numerical translation of long-term foreign-currency credit ratings at the issuer level by S&P. We assign numbers from 1 to 25, corresponding to the S&P ratings range from D (lowest rating and default on debt) to AAA (highest rating) so that a higher value of the numerical ratings indicates a lower expected default risk. *Adj_Rating* is a *Rating* adjusted by +0.5 for a positive outlook or by −0.5 for a negative outlook; no adjustment from the data is made for a stable, developing, or missing outlook. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. *Real GDP* per Capita is the natural logarithm of a country's real GDP per capita (constant 2015 $US) each year from the World Bank database. *Rule of Law* is the yearly rule of law index from The Varieties of Democracy (V-Dem) project. *Creditor Rights is* the composite creditor right index from Djankov et al. (2008). *Financial Development* is the country-level financial development index by the International Monetary Fund (IMF) in a given year. Detailed definitions of unreported firm-level control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

e., [−2; +2]):

$$\text{Credit Rating}_{i,j,t} = \lambda_0 + \lambda_1 \text{Treat} \times \text{Post} + \sum \gamma_i X_{i,t-1} + \sum \theta_j Z_{j,t-1} + \varepsilon_{i,j,t} \tag{3}$$

where *Credit Rating* alternatively denotes our two firm-level rating measures. *Treat* is a dummy that equals one for treated firms in countries hit by either one of the two climate events and zero for the groups of control firms from non-affected countries in our sample. *Post* is a dummy variable that takes the value of one for post-disaster years and zero otherwise. The coefficient of interest is λ_1 on the interaction term, which represents the changes in the effects of climate change on a firm's credit ratings after the event strikes. The DiD regressions include the firm- and country-level controls specified in Eq. (1) together with firm and year-fixed effects to account for firm-level heterogeneity in terms of exposure to these climate shocks.[16]

Table 6 presents the estimated coefficients of the difference-in-differences (DiD) regressions. Panel A reports the results for the 2003 European Heatwave, while Panel B focuses on the 2005 Katrina Hurricane. In Panel A, where we analyze how firms' credit ratings adjusted following the 2003 European Heatwave, we define treatment firms as those located in France, Germany, Spain, Italy, the UK, the Netherlands, Portugal, Belgium, Switzerland, Austria, Finland, Denmark, and Ireland. Due to the limited number of non-U. S. firms in our sample, we employ propensity score matching to select the five closest non-European neighbors (within a caliper of 0.15) for each European firm based on their likelihood of experiencing the treatment in 2003, estimated using a logistic regression model with prior-year control variables from our baseline model. This matching procedure results in a testing sample of 47 European firms and 181 non-European control firms. Table IA3 reports the mean-value balance tests of the covariates used in the PSM procedure, indicating that the matching is successful in balancing most covariates between the treatment and control groups. While there was a significant difference in GDP growth, the overall non-significant χ^2-test suggests that the matching procedure effectively controlled for confounding factors.

Using the matched sample, the estimation results in Columns (1) and (3) of Panel A demonstrate that the Heatwave had a negative impact on firm credit ratings two years after the event, as evidenced by the negative and statistically significant coefficients of the interaction term *Treat* × *Post*. In Columns (2) and (4), we replace the *Treat* × *Post* indicator in Eq. (2) with interaction terms between Treat and event year indicators from (*t* - *2*) to (*t* + *2*) around the event year, using the event year as our reference group.[17] We document insignificant coefficients for the interaction terms *Treat* × *Post (−2)* and *Treat* × *Post (−1),* indicating the absence of a pre-existing

[16] We thank an anonymous referee for making this excellent suggestion to include firm-fixed effects in our DiD models to account for firm-level heterogeneity.

[17] It is important to note that both the 2003 European Heatwave and the 2005 Katrina Hurricane occurred in the third calendar quarter of the respective event years. Hence, we use the event year as the baseline for comparison.

Table 6
Difference-in-differences analysis.

Panel A: 2003 European Heatwave

Variable	(1) *Rating*	(2) *Rating*	(3) *Adj_Rating*	(4) *Adj_Rating*
Treat × Post	−1.798***		−1.791***	
	(0.000)		(0.000)	
Treat × Post (−2)		1.025		0.993
		(0.165)		(0.189)
Treat × Post (−1)		−0.033		−0.033
		(0.966)		(0.967)
Treat × Post (1)		−1.351***		−1.349***
		(0.005)		(0.007)
Treat × Post (2)		−2.198***		−2.216***
		(0.002)		(0.003)
Obs	421	421	421	421
Adj. R^2	0.770	0.775	0.769	0.775
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B: 2005 Katrina Hurricane

Variable	(1) *Rating*	(2) *Rating*	(3) *Adj_Rating*	(4) *Adj_Rating*
Treat × Post	−0.698**		−0.588*	
	(0.024)		(0.051)	
Treat × Post (−2)		0.472		0.492
		(0.114)		(0.116)
Treat × Post (−1)		−0.319		−0.289
		(0.203)		(0.258)
Treat × Post (1)		−0.420**		−0.332*
		(0.038)		(0.092)
Treat × Post (2)		−1.440***		−1.211**
		(0.006)		(0.020)
Obs	2811	2811	2811	2811
Adj. R^2	0.793	0.795	0.800	0.803
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

The table displays the results from the following regression:

$$\text{Credit Rating}_{i,j,t} = \lambda_0 + \lambda_1 \textit{Treat} \times \textit{Post} + \sum \gamma_i X_{i,t-1} + \sum \theta_j Z_{j,t-1} + \varepsilon_{i,j,t}$$

Credit Rating is alternatively one of the two measures, *Rating* and *Adj_Rating*. *Rating* is the numerical translation of long-term foreign-currency credit ratings at the issuer level by S&P. We assign numbers from 1 to 25, corresponding to the S&P ratings range from D (lowest rating and default on debt) to AAA (highest rating) so that a higher value of the numerical ratings indicates a lower expected default risk. *Adj_Rating* is a *Rating* adjusted by +0.5 for a positive outlook or by −0.5 for a negative outlook; no adjustment from the data is made for a stable, developing, or missing outlook. *Treat* is a dummy variable that takes the value of one for firms in countries directly affected by either the 2003 European Heatwave or the 2005 Katrina Hurricane and zero otherwise. *Post* is a dummy variable that equals one for years after disasters (i.e., 2003 or 2005) and zero otherwise. Detailed definitions of unreported firm-level control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. The sample period is from 1997 to 2019. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 7
Instrumental variable analysis.

Variable	(1) *Vulnerability*	(2) *Rating*	(3) *Adj_Rating*
Disaster Deaths	0.007***		
	(0.000)		
%Renewable	−0.000***		
	(0.004)		
Fitted Vulnerability		−32.584***	−32.641***
		(0.000)	(0.000)
IO	−0.010***	0.231*	0.231*
	(0.000)	(0.078)	(0.083)
Debt	−0.007***	−5.099***	−5.145***
	(0.001)	(0.000)	(0.000)
Debt to CF	−0.000**	−0.116***	−0.116***
	(0.024)	(0.000)	(0.000)
IntCoverage	0.000*	−0.000	−0.000
	(0.086)	(0.908)	(0.888)
NegDebt	−0.005***	−3.427***	−3.428***
	(0.003)	(0.000)	(0.000)
Size	0.001***	0.451***	0.451***
	(0.000)	(0.000)	(0.000)
OpMargin	−0.011***	0.967***	0.929***
	(0.000)	(0.002)	(0.003)
Rent	−0.015*	−10.832***	−10.985***
	(0.069)	(0.000)	(0.000)
Tangibility	−0.007***	−0.345	−0.311
	(0.000)	(0.121)	(0.158)
Capex	0.005*	−1.381***	−1.305***
	(0.087)	(0.001)	(0.002)
Std_OpMargin	−0.001*	−1.359***	−1.349***
	(0.058)	(0.000)	(0.000)
GDP Growth	0.002***	0.083**	0.079*
	(0.006)	(0.046)	(0.060)
Inflation	0.000	−0.194***	−0.185***
	(0.583)	(0.000)	(0.000)
Pstability	−0.028***	−0.447	−0.444
	(0.000)	(0.119)	(0.120)
Obs	15,362	15,362	15,362
Adj. R^2	0.537	0.949	0.948
p-value of Hansen *J*-stat		0.173	0.170
Kleiberg-Paap *F*-tests	67.92		
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

This table reports the estimated coefficients of instrumental variable regressions as specified in Eq.(4). Column (1) reports the first-stage regression of the climate change vulnerability index on the death toll due to climate disasters in a country during a year. Columns (2) and (3) estimate the second-stage regressions of credit rating measures on the instrumented vulnerability index. *Rating* is the numerical translation of long-term foreign-currency credit ratings at the issuer level by S&P. We assign numbers from 1 to 25, corresponding to the S&P ratings range from D (lowest rating and default on debt) to AAA (highest rating) so that a higher value of the numerical ratings indicates a lower expected default risk. *Adj_Rating* is a *Rating* adjusted by +0.5 for a positive outlook or by −0.5 for a negative outlook; no adjustment from the data is made for a stable, developing, or missing outlook. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. *Disaster Deaths* is the log transformation of the number of deaths from climate disasters reported from the Our World in Data website. *%Renewable* is a country's share of primary energy consumption from renewable sources in a given year sourced from Energy Institute – Statistical Review of World Energy. Detailed definitions of control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. The sample period is from 1997 to 2019. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

trend prior to the event. These findings validate the suitability of our DiD approach. Figure IA1 visually represents these estimated coefficients.[18]

In Panel B, we focus on the impact of the 2005 Katrina Hurricane on credit ratings among U.S. firms relative to other firms in our sample. Given the predominance of U.S. firms in our dataset, we deliberately use all non-U.S. firms as control groups for this analysis. Similar to Panel A, we report the estimation results of the DiD regression in Columns (1) and (3), followed by a breakdown of the *Treat* × *Post* indicator into individual event year indicators. Again, we document a negative and statistically significant coefficient on *Treat* × *Post*, suggesting that U.S. firms were perceived as less credible following the hurricane compared to non-U.S. firms. Also, the results in Columns (2) and (4) imply that there exists no pre-existing difference between these two subgroups before the event.

4.3.3. Instrumental variable (IV) approach

The downside of the DiD approach in the previous subsection is the small sample due to the limited number of countries influenced by climate disasters over a pre-specified window of time. We thus complement these identification tests with IV analysis. Specifically, an IV in the context of this study should strongly correlate with climate change vulnerability but not directly affect credit ratings. From the Our World in Data website, we collect information about two potential instruments. The first one is the natural logarithm of the number of deaths from drought, floods, and extreme temperatures in a country *j* in year *t-1*, denoted as *Disaster Deaths*, and the second instrument is a country's share of primary energy consumption from renewable sources (*%Renewable*) in year *t-1*.

We expect that the number of deaths from climate disasters and the extent of renewable energy consumption can reasonably meet the restrictions of an instrumental variable for two main reasons. Firstly, they can serve as proxies for a country's climate change vulnerability, reflecting factors such as human capital and environmental policy efforts. Therefore, one might anticipate a strong correlation between the IV and the endogenous climate vulnerability variable. Second, in the existing literature, we are unaware of evidence for a direct link between credit ratings, the number of people who die in natural disasters, and the share of renewable energy in total energy consumption.

Given the above qualities, we re-estimate our baseline regressions using a two-stage least squares (2SLS) estimator specified below:

$$\begin{aligned} &1st\ stage: Vulnerability_{j,t-1} = \alpha_0 + \alpha_1 IVs_{j,t-1} + \sum \varphi_i X_{i,t-1} + \sum \mu_j Z_{j,t-1} + \varepsilon_{i,j,t} \\ &\text{2nd stage}: \text{Credit Rating}_{i,j,t} = \beta_0 + \beta_1 \widehat{\text{Vulnerability}}_{j,t-1} + \sum \gamma_i X_{i,t-1} + \sum \theta_j Z_{j,t-1} + \varepsilon_{i,j,t} \end{aligned} \tag{4}$$

The estimated coefficients of the first-stage regression are presented in Column (1) of Table 7. Consistent with our prior, *Vulnerability* significantly increases with *DisasterDeaths* and decreases with *%Renewable*. The first-stage Kleiberg-Paap *F*-statistic is 67.92, suggesting that our specification is unlikely to be subject to the weak identification problem.

Columns (2) and (3) display the second-stage regression results, where the dependent variables are *Rating* and *Adj_Rating*, respectively. After controlling for endogeneity, the instrumented *Vulnerability* remains negatively and significantly associated with both credit rating proxies. The magnitude of the *Vulnerability* coefficient in 2SLS regressions is considerably larger (i.e., more negative) than those in OLS regressions, indicating that the OLS estimator might have biased the coefficient estimates upward due to potential omitted-variable problems. We also report the Sargan-Hansen *J*-test *p*-values at the bottom of the table, which are all greater than 0.10, to justify the validity of our instruments.

Collectively, our results from the DiD and IV analyses are consistent with a causal relationship between climate change risks and firm-level credit ratings. However, we acknowledge that none of our identification strategies above is bulletproof. For instance, the death toll of climate disasters might jeopardize a firm's operations, reduce fundamental values, and lead to rating downgrades, which possibly contravenes the exclusion restriction of an IV. As such, we want to alarm future research to be cautious when interpreting the causal impact of climate change vulnerability on credit ratings from our study.

4.4. Economic channels

We dedicate this subsection to exploring the underlying mechanisms through which climate change vulnerability induces credit rating agencies to lower their assessment of a firm's creditworthiness. In particular, we evaluate whether credit rating agencies are concerned with new information on a firm's default status resulting from climate change factors. We employ four proxies for firms' fundamentals to test this question, including two default risk measures, cash flow volatility and earnings volatility. Specifically, we construct Merton's (1974) distance-to-default (*DTD*) and Bharath and Shumway's (2008) expected default frequency (*EDF*) as measures for a firm's risk of default. We obtain the monthly *DTD* from the Credit Research Initiative (CRI) database built on the forward intensity model Duan, Sun, and Wang (2012) developed for multiperiod default prediction.

Specifically, the daily *DTD* values from the CRI are rooted in the traditional Kealhofer-Merton-Vasicek (KMV) estimation model as follows:

[18] Of note, we consolidate our identification strategies with a placebo test for the DiD analysis to mitigate the effects of time-varying factors. Specifically, we create the pseudo-event year of 1999 for the 2003 European heatwave and re-estimate our DiD regressions using a sample period of two years before and after 1999. The reasons for our selection of this pseudo-event year are that we have been observing the occurrence of heatwaves more frequently, and their effects now last longer, thereby making the selection of a pseudo-event year later than 2003 confound the placebo test. Table IA4 shows that the coefficient on the interaction term *Treat* × *Post* is not statistically significant when the pseudo-event year is 1999, indicating that our DiD analysis is unlikely to be spurious.

$$DTD = \frac{ln\left(\frac{V_t}{L}\right) + \left(\mu - \frac{\sigma^2}{2}\right)(T-t)}{\sigma\sqrt{T-t}} \tag{5}$$

where V_t is a firm's market value estimated using a geometric Brownian motion with drift μ and volatility σ; μ represents the short-term risk-free rate; and σ captures the firm's stock return volatility using the standard deviation of its market-adjusted returns. The default point, L, equals short-term liabilities $+$ (0.5 $\times$ long-term liabilities). $\sqrt{T-t}$ is set to 1 year. However, the CRI follows Duan et al. (2012) and implements some adjustments to its DTD estimation.[19] These adjustments are: (i) adding a fraction (δ) of other liabilities to the KVM default point L, estimated at a sectoral level for each calibration group[20]; (ii) setting μ equal to $\sigma^2/2$ to improve the stability of the DTD measure; and (iii) standardizing the firm's market value by its book value to handle the scale change due to any significant investment and financing actions. The higher the CRI distance-to-default (*DTD*) value, the larger the positive spread between firm value and firm liabilities and the lower the probability of default.

We then use the cumulative normal distribution of the negative distance-to-default to estimate *EDF* (Bharath & Shumway, 2008; Brogaard, Li, & Xia, 2017). We also consider two other measures for fundamental volatilities to capture the financial instability brought by climate change. We measure cash flow volatility (*CFVol*) as the standard deviation of five years' operating cash flows, scaled by the five-year average total assets. In addition, we compute earnings volatility (*EarningsVol*) as the standard deviation of five years' earnings before interest and tax, scaled by the five-year average total assets.

We present the regression estimates of firm fundamentals on the climate change vulnerability index in Table 8. Column (1) shows a significantly negative coefficient of *Vulnerability* on a firm's distance to default, suggesting that firms more sensitive to climate change are subject to greater default risk. Consistently, we document an increase in expected default frequency (*EDF*) in firms with higher exposure to climate change risks. Besides the increased level of default risk associated with climate change vulnerability, the estimation results in Columns (3) and (4) also show that firms in countries facing climate change risks experience higher cash flow and earnings volatilities. Combined, the results in Table 8 provide some evidence that rating agencies' consideration of climate change vulnerability in credit assessment could have been the outcome of this factor's adverse impacts on client firms' financial position.

5. Additional analyses

5.1. Cross-sectional analysis

We corroborate the economic implications of this study by looking into the heterogeneous effects of climate change vulnerability on credit ratings based on country-level institutions.

We contend that the impact of climate change on credit ratings could be less acute for issuers in countries with strong creditor rights. To test this notion, in Columns (1) and (2) of Table 9, we extend the baseline regression with an interaction term between *Vulnerability* and *Creditor Rights* (as previously defined in footnote 15 of section 4.3.1). Two results are of note. First, we find that firms more vulnerable to climate change are subject to lower credit ratings, consistent with the main findings. Second, the regression coefficients on the interaction term between *Vulnerability* and *Creditor Rights* are significantly positive at the 5 % level. This result implies that firms operating in countries with better creditor protection are less exposed to the downgrading effect of climate change vulnerability on their credit ratings.

We continue the analysis by exploring the role of government in moderating the relationship between climate change vulnerability and firm-level credit ratings. We argue that transitional risk is higher for firms operating in countries with stronger government commitments to reduce climate change. As such, the effect of climate change risks on credit ratings can be more pronounced for those firms. To test that conjecture, we employ the variable *Government Effectiveness,* the World Bank's government effectiveness index, which captures the quality of policy formulation and implementation and the credibility of the government's commitment to such policies. Our baseline model then incorporates the interaction term between *Vulnerability* and *Government Effectiveness*. Columns (3) and (4) exhibit that the coefficient estimates on the interaction term between *Vulnerability* and *Government Effectiveness* are positive and significant at the 1 % level. The evidence indicates that firms from countries with higher government commitment to policies that may help resolve climate change are more likely to receive lower ratings.

Next, we study whether environmental technologies may moderate the interplay between climate change vulnerability and credit ratings. We construct the variable *Environmental Technologies* as a country's number of patents in environment-related technologies reported by the Organisation for Economic Co-operation and Development (OECD). The interaction term between *Vulnerability* and *Environmental Technologies* is then included in the baseline regression model. In Columns (5) and (6), we document that while a higher level of climate change vulnerability costs firms a lower credit rating, those from countries with better environmental technologies experience such rating impact to a lower extent. The result of this analysis is consistent with the anecdotal evidence that developing and using emerging green technologies help firms improve their competitiveness, such as in production and distribution costs, thereby

[19] Duan et al. (2012) provide comprehensive evidence suggesting that this method of estimating *DTD* outperformance the traditional destination technique.

[20] See Duan et al. (2012)'s Appendix B for the details of the estimation process.

Table 8
Climate change vulnerability and firm fundamentals.

	(1)	(2)	(3)	(4)
Variable	*DTD*	*EDF*	*CFVol*	*EarningsVol*
Vulnerability	−1.614**	0.119***	0.134***	0.042*
	(0.011)	(0.000)	(0.000)	(0.092)
IO	4.072***	−0.106***	−0.035***	−0.033***
	(0.000)	(0.000)	(0.000)	(0.000)
Debt	−5.161***	0.153***	−0.011***	−0.017***
	(0.000)	(0.000)	(0.000)	(0.000)
Debt to CF	−0.018***	0.001***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
IntCoverage	0.000***	0.000***	−0.000***	−0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
NegDebt	−1.333***	0.069***	0.021***	0.031***
	(0.000)	(0.000)	(0.000)	(0.000)
Size	0.062***	−0.003***	−0.010***	−0.012***
	(0.000)	(0.000)	(0.000)	(0.000)
OpMargin	0.099***	−0.001***	−0.002***	−0.004***
	(0.000)	(0.001)	(0.000)	(0.000)
Rent	−1.378**	0.054***	0.073***	0.106***
	(0.012)	(0.002)	(0.000)	(0.000)
Tangibility	0.938***	−0.012***	−0.073***	−0.061***
	(0.000)	(0.000)	(0.000)	(0.000)
CapEx	0.802***	−0.051***	0.077***	0.064***
	(0.000)	(0.000)	(0.000)	(0.000)
Std_OpMargin	0.011***	−0.001***	0.002***	0.003***
	(0.001)	(0.001)	(0.000)	(0.000)
GDP	0.045***	−0.004***	−0.001***	−0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Inflation	−0.151***	0.006***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Pstability	−0.391***	0.011***	0.005***	0.011***
	(0.000)	(0.000)	(0.001)	(0.000)
Obs	185,425	185,425	411,623	455,586
Adj. R^2	0.304	0.206	0.240	0.282
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table examines the relationship between climate change vulnerability and corporate fundamentals to uncover the mechanisms underlying the adverse impacts of climate change risks on credit ratings. *DTD* is Merton's (1974) distance-to-default estimated using the model by Duan et al. (2012). *EDF* is the expected default frequency, measured using the cumulative normal distribution of the negative distance-to-default following Bharath and Shumway (2008). *CFVol* is the standard deviation of five years' operating cash flows, scaled by the five-year average total assets. *EarningsVol* is the standard deviation of five years' earnings before interest and tax, scaled by the five-year average total assets. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. Detailed definitions of control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. The sample period is from 1997 to 2019. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

boosting the demand for their products and services.[21] This finding highlights the role of environmental innovation in tackling the negative effects of climate change vulnerability.

Lastly, we investigate whether credit rating agencies' local presence plays a role in constituting the association between climate change vulnerability and credit ratings. From the exposure to the effect of climate change through their local offices, credit rating agencies with local presence are directly exposed to adverse consequences of climate change and incorporate these negative facets in assessing their clients' credit quality to a greater degree. As a result, the negative effect of climate change vulnerability on credit ratings is likely to be stronger when rating agencies have an office local to their client firms. To test this conjecture, we construct *S&P Office* as an indicator variable that takes the value of one for 35 countries with S&P offices and zero otherwise.[22] We then add the interaction term between *Vulnerability* and *S&P Office* to the baseline Eq. (1) and report the estimation results in Columns (7) and (8). We find that the effect of climate change vulnerability is incorporated more heavily in assessing a firm's creditworthiness when that firm is physically proximate to a local S&P office. This evidence supports the argument that the exposure of their regional offices to climate

[21] For example, in 2017, West China Cement Ltd. implemented an eco-friendly waste heat recycling system that helps the company to save electricity costs. Their credit rating was upgraded to B+ as a result.

[22] The information about S&P office locations can be found at: https://www.spglobal.com/en/contact-us/office-locations (retrieved on August 9, 2022).

Table 9
Cross-sectional analyses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Variable	*Rating*	*Adj_Rating*	*Rating*	*Adj_Rating*	*Rating*	*Adj_Rating*	*Rating*	*Adj_Rating*
Vulnerability	−9.638**	−9.944**	0.212	0.151	−17.876***	−17.447***	4.706*	4.534*
	(0.015)	(0.013)	(0.939)	(0.957)	(0.000)	(0.000)	(0.067)	(0.080)
Vulnerability × Creditor Rights	3.745**	3.871**						
	(0.030)	(0.026)						
Creditor Rights	−0.629	−0.669						
	(0.247)	(0.221)						
Vulnerability × Government Effectiveness			−7.746***	−7.714***				
			(0.000)	(0.000)				
Government Effectiveness			2.122***	2.120***				
			(0.006)	(0.007)				
Vulnerability × Environmental Technologies					1.243***	1.194***		
					(0.000)	(0.001)		
Environmental Technologies					−0.387***	−0.368***		
					(0.003)	(0.005)		
Vulnerability × S&P Office							−15.845***	−15.673***
							(0.000)	(0.000)
S&P Office							5.504***	5.464***
							(0.000)	(0.000)
Obs	16,002	16,002	16,206	16,206	16,177	16,177	16,206	16,206
Adj. R^2	0.349	0.349	0.337	0.337	0.335	0.335	0.337	0.337
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table shows how the impact of climate change vulnerability on credit ratings varies with country-level institutional factors and geographical locations. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. *Creditor Rights is* the composite creditor right index from Djankov et al. (2008). *Government Effectiveness* is the World Bank's government effectiveness index, which captures the quality of policy formulation and implementation and the credibility of the government's commitment to such policies. *Environmental Technologies* is a country's number of patents in environment-related technologies. *S&P Office* is a dummy variable that takes the value of one for firms located in one of 35 countries with S&P offices and zero otherwise. *Rating* is the numerical translation of long-term foreign-currency credit ratings at the issuer level by S&P. We assign numbers from 1 to 25, corresponding to the S&P ratings range from D (lowest rating and default on debt) to AAA (highest rating) so that a higher value of the numerical ratings indicates a lower expected default risk. *Adj_Rating* is a *Rating* adjusted by +0.5 for a positive outlook or by −0.5 for a negative outlook; no adjustment from the data is made for a stable, developing, or missing outlook. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. Detailed definitions of control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. The sample period is from 1997 to 2019. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

change induces credit rating agencies to pay closer attention and put a heavier weight on climate change issues in their credit assessment.

The empirical tests in Table 9 show that the effect of climate change vulnerability on firm credit ratings is heterogeneous across countries. More specifically, the impact weakens in countries with better creditor protection and environmental technologies. Yet, it increases in those with greater government effectiveness in stipulating nationwide policy and local presence of credit rating agencies.

5.2. *Market implications*

The empirical evidence in the existing literature contends that credit ratings are an integral component of debt capital markets (i.e., bond and credit default swap (CDS) markets). For instance, Galil, Shapir, Amiram, and Ben-Zion (2014) find that credit ratings explain cross-sectional variation in CDS spreads even after controlling for firm fundamentals. Similarly, several papers suggest that a firm's ratings affect its bond yields and cost of debt financing, given the information ratings convey about its default risk (e.g., Kisgen & Strahan, 2010; Kliger & Sarig, 2000). Having shown that climate change vulnerability leads to lower ratings due to increased fundamental volatility and greater risk of default, we next explore how CDS traders and credit analysts respond to the changes in credit ratings due to climate change.

First, we ask whether CDS traders, through the observed effect on credit ratings, consider pricing a reference entity's climate change vulnerability in their CDS contracts. To test this conjecture, we collect CDS pricing data from the Markit database and construct a new variable, denoted as *CDS Spread*, which is estimated as the median conventional spread of all 5-year CDS contracts, taking it as the reference entity. We then regress the *CDS Spread* on our climate change vulnerability index and report the estimated regressions in Columns (1) of Table 10. To ensure that country-level structural factors do not spuriously drive the relationship between *CDS Spread* and *Vulnerability*, we control for institutional variables, including real GDP per capita, the rule of law, and financial development along with country-fixed effects in Column (2).[23] Across two columns, we find that the coefficient of *Vulnerability* on *CDS Spread* is positive and statistically significant, implying that it is more costly for CDS buyers to hold swaps on reference firms vulnerable to climate challenges. This evidence is congruent with our previous results that climate change vulnerability increases firms' probability of default and, thus, makes CDS contracts more valuable.

Second, we study whether credit analysts consider lower ratings due to greater exposure to climate change when pricing corporate loans. We collect bank loan information from DealScan and employ the initial all-in-drawn spread over the London Interbank Offer Rate (or LIBOR) as our proxy for a firm's cost of debt (denoted as *Bank Loan Spread*). This spread is the amount a firm pays in basis points over LIBOR for each loan dollar drawn down from a lending facility. It includes the spread of the loan and any annual or facility fees paid to the bank group. For regression analysis, the spread is log-transformed to tackle positive skewness in the data because firms having spreads less than LIBOR are unlikely to receive loans. Columns (3) and (4) of Table 10 display the regressions of *Bank Loan Spread* on *Vulnerability* estimated at the lending facility level. These models include additional controls for loan-specific characteristics: loan size, maturity, security, and whether the loan has a covenant. The detailed definitions of these controls are in Appendix A. We document a significantly positive relationship between climate change vulnerability and bank loan spreads, consistent with our prior results. This result suggests that climate change risks, through their adverse impacts on credit ratings, matter in the credit assessment of lending institutions and increase the firm's cost of debt.

5.3. Corporate responses to climate change risks

In this section, we explore what financial tactics climate-vulnerable firms can use to alleviate the concerns about unfavorable credit assessments. The precautionary motive theory proposes that firms with limited access to capital markets find it beneficial to hold more cash or to save as a cushion (e.g., Bates, Kahle, & Stulz, 2009; Harford, Klasa, & Maxwell, 2014; McLean, 2011; Opler, Pinkowitz, Stulz, & Williamson, 1999). Therefore, with greater exposure to climate challenges, firms are expected to increase their precautionary saving and are less likely to distribute their profits as dividends to shareholders to mitigate the negative valuation of credit rating agencies. To test this conjecture, we examine the role of cash holdings and payout policies in moderating the interplay between climate change and credit ratings.

We introduce two new variables in this line of inquiries: the level of cash holdings (*Cash*), which is the ratio of cash or cash equivalents to the book value of total assets, and *Dividend*, which is an indicator variable that takes the value of one if firms pay dividends in a given fiscal year and zero otherwise. In the baseline regression model, we then include the interaction terms between Vulnerability and these two variables. The estimated coefficients of extended regressions are reported in Columns (1) to (4) of Table 11. Two findings are noteworthy. First, we consistently document negative *Vulnerability* coefficients on credit rating measures in Columns (1) and (2), suggesting that greater exposure to climate change leads to lower credit ratings. Second, the coefficients of the interaction terms indicate that the effects of climate change vulnerability on credit ratings are weaker among firms that hold more cash and are less likely to pay out earnings as dividends. Overall, the evidence supports that companies can effectively mitigate the negative effect of climate change vulnerability on their credit ratings by increasing their cash holdings and reducing dividend payouts.

5.4. Subsample analyses

5.4.1. Time-series variation

In addition to the cross-sectional heterogeneity in how climate change vulnerability impacts credit ratings, we further explore the time-series variation in the effect in the context of major international climate change conferences. Specifically, we focus on the Kyoto Protocol (1997), the Doha Climate Change Conference (2012), and the Paris Agreement (2015). These events mark significant milestones in global climate policy, with the Kyoto Protocol and the Paris Agreement establishing greenhouse gas emission limits, whereas the Doha Conference failed to achieve a similar agreement. Hence, we hypothesize that the Kyoto Protocol and the Paris Agreement will induce rating agencies to pay more attention to firms' climate change vulnerability. In contrast, the unsuccessful Doha Conference may lead to less attention. To test these hypotheses, we analyze three time-series subsamples: 1997–2011, 2012–2015, and 2016–2019. The results are presented in Panel A of Table 12.

Results from Columns (1) and (2) suggest that, following the ratification of the Kyoto Protocol, a negative and significant relationship exists between climate change vulnerability and credit ratings. However, in Columns (3) and (4), there is not enough evidence to suggest that rating agencies incorporate climate change vulnerability in creditworthiness assessment by rating agencies after the failure of the 2012 United Nations Climate Change Conference. In Columns (5) and (6), we document the significantly negative impact of climate change vulnerability on credit ratings. These findings suggest that considering climate change vulnerability in rating agencies' credit health assessment varies over time, depending on the outcomes of significant climate change summits.

5.4.2. Subsample analysis

Our final empirical test investigates the differential impact of climate change vulnerability on credit ratings across developed and emerging markets. To conduct this investigation, we partitioned our sample into two distinct groups: 28 developed economies and 32 emerging economies, as categorized by the World Economic Outlook Database of the International Monetary Fund. Then, we re-

[23] Note that we did not control for creditor rights in this analysis since this variable is absorbed by country fixed effects.

Table 10
Climate change vulnerability and its implications on the debt market.

Variable	(1) *CDS Spread*	(2) *CDS Spread*	(3) *Bank Loan Spread*	(4) *Bank Loan Spread*
Vulnerability	0.145***	0.101*	0.061**	0.157**
	(0.009)	(0.071)	(0.022)	(0.048)
Log(Loan Size)			−0.003***	−0.003***
			(0.000)	(0.000)
Log(Maturity)			0.001	0.001*
			(0.112)	(0.059)
Secure			0.009***	0.009***
			(0.000)	(0.000)
Covenant			−0.000	−0.000
			(0.610)	(0.657)
GDP per capita		−0.057**		0.027*
		(0.026)		(0.091)
Rule of Law		−0.075		0.001
		(0.330)		(0.978)
Financial development		0.015		−0.008
		(0.731)		(0.637)
Obs	3027	3023	15,925	15,923
Adj. R^2	0.097	0.100	0.491	0.496
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Country FE	No	Yes	No	Yes
Year FE	Yes	Yes	Yes	Yes

This table examines the effects of climate change vulnerability on the credit default swaps (CDS) spread (*CDS Spread*) and the cost of bank debt (*Bank Loan Spread*). *CDS Spread* is the median conventional spread of all 5-year CDS contracts taking a given firm *i* as the reference entity. *Bank Loan Spread* is the amount a firm *i* pays in basis points over LIBOR for each loan dollar drawn down from a lending facility. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. Detailed definitions of control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. The sample period is from 1997 to 2019. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 11
Corporate responses to the impacts of climate change vulnerability on credit ratings.

Variable	(1) *Rating*	(2) *Adj_Rating*	(3) *Rating*	(4) *Adj_Rating*
Vulnerability	−9.913***	−9.808***	0.993	1.016
	(0.000)	(0.000)	(0.762)	(0.758)
Vulnerability × Cash	42.169***	40.536***		
	(0.006)	(0.009)		
Cash	−16.715***	−16.202***		
	(0.001)	(0.002)		
Vulnerability × Dividend			−7.531**	−7.599**
			(0.018)	(0.017)
Dividend			4.116***	4.128***
			(0.000)	(0.000)
Obs	13,784	13,784	14,342	14,342
Adj. R^2	0.401	0.400	0.425	0.423
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

This table investigates corporate tactics firms can adopt to mitigate the negative impact of climate change vulnerability on credit ratings. We define two corporate strategy variables: *Cash* and *Dividend*. *Cash* is the ratio of cash or cash equivalents to the book value of total assets. *Dividend* is an indicator variable that takes the value of one if firms pay out dividends to common equity in a given fiscal year and zero otherwise. *Rating* is the numerical translation of long-term foreign-currency credit ratings at the issuer level by S&P. We assign numbers from 1 to 25, corresponding to the S&P ratings range from D (lowest rating and default on debt) to AAA (highest rating) so that a higher value of the numerical ratings indicates a lower expected default risk. *Adj_Rating* is a *Rating* adjusted by +0.5 for a positive outlook or by −0.5 for a negative outlook; no adjustment from the data is made for a stable, developing, or missing outlook. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. Detailed definitions of unreported control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. The sample period is from 1997 to 2019. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

Table 12
Subsample analyses.

Panel A: Sub-period analysis

.	1997–2011		2012–2015		2016–2019	
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	*Rating*	*Adj_Rating*	*Rating*	*Adj_Rating*	*Rating*	*Adj_Rating*
Vulnerability	−0.065***	−0.063***	0.006	0.000	−0.051**	−0.053**
	(0.000)	(0.000)	(0.764)	(0.998)	(0.029)	(0.022)
Obs	10,874	10,874	2923	2923	2406	2406
Adj. R^2	0.332	0.331	0.363	0.363	0.349	0.352
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Sub-sample analysis

	Rating		*Adj_Rating*	
	(1)	(2)	(3)	(4)
Variable	Developed	Emerging	Developed	Emerging
Vulnerability	−13.275***	−3.944*	−13.184***	−4.408*
	(0.000)	(0.100)	(0.000)	(0.065)
χ^2 (β[Developed] – β[Emerging])	5.69**		5.01**	
Obs	14,634	1567	14,634	1567
Adj. R^2	0.368	0.299	0.368	0.293
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel A of this table shows variations in the effect of climate change vulnerability on credit ratings during different time episodes (e.g., 1997 to 2011, 2012 to 2015, and 2016 to 2019), corresponding to outcomes of key climate change conferences: 1997 United Nations Framework Convention on Climate Change in Kyoto (Japan), the 2012 United Nations Climate Change Conference in Doha (Qatar), and the 2015 United Nations Climate Change Conference in Paris (France). Panel B displays the estimated effect of climate change vulnerability for two subsamples of developed and emerging markets based on the classification of the World Economic Outlook Database by IMF. *Vulnerability* is the climate change vulnerability index constructed by ND-GAIN. Detailed definitions of unreported control variables are provided in Appendix A. We winsorize all continuous variables at the 1 % level in both distribution tails. Fixed effects are indicated in each column. Standard errors are clustered in country and year levels. We report *p*-values in parentheses. The sample period is from 1997 to 2019. *Obs* denotes the number of observations. *, **, and *** indicate significance at the 10 %, 5 %, and 1 % levels, respectively.

estimated our baseline regression model for each of these subsamples. The estimation results are reported in Panel B of Table 12. We document that the effects of climate change vulnerability are more pronounced for firms in developed markets relative to their counterparts in emerging markets, supported by statistically significant χ^2 statistics for the difference in V*ulnerability* coefficients across the two groups. This observation supports the notion that developed markets have more stable economies and sophisticated information channels, fostering greater awareness of long-term issues such as climate change.

6. Conclusion

In this study, we provide global-scale evidence that climate change vulnerability is an essential constituent of corporate credit ratings. Specifically, our results show that firms in countries with higher exposure to climate change are likelier to receive lower ratings. Consequently, these firms face a higher barrier to accessing debt financing and are viewed as less financially viable by other debt market participants. We also find that companies can strategically adjust their cash holding and dividend payout policy to mitigate the negative impact of climate-change-related risks on their credit ratings. In addition, the cross-sectional analyses reveal that firms operating in countries with more creditor protection, better environmental technologies, and lower government commitment to climate targets are less exposed to the effect of climate change vulnerability on their ratings.

Our findings hold several implications for CRAs, regulators, and corporations. First, despite CRAs' commitment to considering climate change risks in their credit assessment, there is still insufficient information on how these risks influence rating outcomes. In addition, CRAs have not always separated climate change from other environmental, social, and governance (ESG) factors, making it difficult to assess the stand-alone impact of climate change vulnerability on their ratings. CRAs should improve methodological transparency and comparability, especially across different institutional settings, to enable investors to make informed investment decisions.

Second, we advocate for policymakers to implement more stringent regulations requiring firms to disclose their environmental risks. Specifically, policymakers should mandate the disclosure of climate risk exposures and impacts in financial reports, aligning with frameworks like the TCFD. Regulatory bodies should also enhance oversight of compliance and ensure the effectiveness of disclosure requirements through regular reviews and adjustments. Governments and regulators should provide incentives for firms that proactively manage and disclose climate risks, such as tax benefits or reduced borrowing costs. Fostering collaboration between credit rating agencies, policymakers, and international bodies will help develop harmonized climate risk assessment standards and ensure a co-ordinated approach to managing these risks.

Third, firms should be cognizant of the potential negative consequences of climate change on their credit ratings, which could impair their ability to borrow and increase borrowing costs. To mitigate these risks, firms should strategically design their corporate decisions to manage the impacts of climate change on their creditworthiness.

Despite the implications discussed above, we would like to acknowledge that our analysis does not examine how firm-level exposure to climate risk influences credit ratings in an international context. There may be distinctive firm-level attributes that offer more insightful perspectives on the relationship between climate-related risks and credit assessments compared to a country-level study. Future research could explore this avenue, as well as considering other aspects of corporate performance and investor behavior, to provide a more comprehensive understanding of climate-related risks.

CRediT authorship contribution statement

Harvey Nguyen: Writing – review & editing, Writing – original draft, Methodology, Data curation, Conceptualization. **Anh Viet Pham:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Man Duy Pham:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Mia Hang Pham:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation, Conceptualization.

Declaration of competing interest

One of the co-authors, Dr. Harvey Nguyen, is an Editorial Board Member of Global Finance Journal and was not involved in the editorial review or the decision to publish this article. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Variable Definitions

Variable	Definition	Data source
Credit rating measures		
Rating	The numerical translation of S&P foreign currency long-term issuer-level ratings. The value ranges from 1 to 25, corresponding to the S&P rating of D to AAA	S&P Capital IQ
Adj_Rating	The numerical rating adjusted by +0.5 for a positive outlook or by −0.5 for a negative outlook; no adjustment is made for stable, developing, or missing outlook from the data	S&P Capital IQ
Investment Grade	A dummy variable equals one if a firm's credit rating is BBB- or better and zero otherwise	S&P Capital IQ
EJR	The numerical translation of issuer-level credit ratings issued by Egan Jones	Egan Jones Ratings Co.
Climate change vulnerability measures		
Vulnerability	The climate change vulnerability index from ND-GAIN	ND-GAIN
ND-GAIN Score	The global adaptation index from ND-GAIN accounts for a country's vulnerability to climate change and its readiness to cope with climate events	ND-GAIN
WSJ Climate Change News Index	The intensity of climate news coverage in the Wall Street Journal developed by Engle et al. (2020)	Engle et al. (2020)
Control variables		
IO	The proportion of a firm's shares held by institutional investors	Factset Ownership
Debt	The sum of long-term debt and short-term debt scaled by the book value of total assets	Compustat Global & North American
Debt to CF	The sum of long-term debt and short-term debt scaled by operating cash flows	Compustat Global & North American
NegDebt	A dummy variable that equals one if Debt to CF is negative and zero otherwise	Compustat Global & North American

(*continued on next page*)

(*continued*)

Variable	Definition	Data source
IntCoverage	Operating income before depreciation and amortization divided by interest expense	Compustat Global & North American
Size	The natural logarithm of the book value of total assets	Compustat Global & North American
OpMargin	Operating income before depreciation and amortization divided by sales	Compustat Global & North American
Std_OpMargin	The standard deviation of operating profit margin over the past five years	Compustat Global & North American
Rent	The rental expense divided by the book value of total assets	Compustat Global & North American
Tangibility	The net value of property, plant, and equipment, scaled by the book value of total assets	Compustat Global & North American
CapEx	Capital expenditures divided by the book value of total assets	Compustat Global & North American
Country-level attributes		
Inflation	A country's inflation rate	World Bank
GDP	A country's gross domestic product growth	World Bank
Real GDP per capital	A country's real GDP per capita computed at 2015 constant $US	World Bank
Pstability	The political stability index from World Bank	World Bank
Rule of Law	The yearly rule of law index from The Varieties of Democracy (V-Dem) project	Our World in Data
Creditor Rights	The composite creditor right index from Djankov et al. (2008). The index ranges from 0 to 4, and one point is added to the index when a country's laws and regulations provide each of the four powers secured lenders have in the event of bankruptcy.	Djankov et al. (2008)
Financial Development	A country's financial development index by International Monetary Fund (IMF) in a given year	IMF
Government Effectiveness	The World Bank's government effectiveness index captures the quality of policy formulation and implication and the credibility of the government's commitment to such policies	World Bank
Environmental Technologies	A country's number of patents in environment-related technologies	OECD database
Variables for identification strategies		
Treat	A dummy variable equals one for firms in countries affected by the 2003 European Heatwave or the 2005 Katrina Hurricane.	Self-generated
Post	A dummy variable equals one for years after disasters (i.e., 2003 and 2005) and zero otherwise	Self-generated
Disaster Deaths	The natural logarithm of the number of deaths from climate disasters	Our World in Data
%Renewable	A country's share of primary energy consumption from renewable sources in a given year from Energy Institute - Statistical Review of World Energy	Our World in Data
Economic channel variables		
DTD	Merton's (1974) distance-to-default using the model by Duan et al. (2012)	Credit Research Initiative (CRI)
EDF	The cumulative normal distribution of negative distance-to-default	Credit Research Initiative (CRI)
CFVol	The standard deviation of operating cash flows over the past five years, scaled by the average value of total assets	Compustat Global & North American
EarningsVol	The standard deviation of earnings before interest and tax over the past five years, scaled by the average value of total assets	Compustat Global & North American
Market implication variables		
CDS Spread	The median value of conventional spreads of all five-year CDS contracts related to firm *i* in a given year.	IHS Markit
Bank Loan Spread	The amount a firm pays in basis points over LIBOR for each loan dollar drawn down from a lending facility	Dealscan
Corporate responses		
Cash	The ratio of cash or cash equivalents to the book value of total assets.	Compustat Global & North American
Dividend	An indicator variable takes the value of one if firms pay dividends to common equity-holders in a given fiscal year and zero otherwise.	Compustat Global & North American
Other variables		
S&P Office	A dummy variable takes the value of one for firms located in one of 35 countries with S&P offices and zero otherwise.	S&P's website

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gfj.2024.101073.

Data availability

Data will be made available on request.

References

Agarwala, M., Burke, M., Klusak, P., Kraemer, M., & Mohaddes, K. (2022). Rising temperatures, falling ratings: The effect of climate change on sovereign creditworthiness (No. 158). In *IMFS Working Paper Series*.

Alok, S., Kumar, N., & Wermers, R. (2020). Do fund managers misestimate climatic disaster risk. *The Review of Financial Studies, 33*(3), 1146–1183.

Ashbaugh-Skaife, H., Collins, D. W., & LaFond, R. (2006). The effects of corporate governance on firms' credit ratings. *Journal of Accounting and Economics, 42*(1–2), 203–243.

Attig, N., Driss, H., & El Ghoul, S. (2020). Rating standards around the world: A puzzle? *Emerging Markets Review, 45*, Article 100701.

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2007). Momentum and credit rating. *The Journal of Finance, 62*(5), 2503–2520.

Baghai, R. P., Servaes, H., & Tamayo, A. (2014). Have rating agencies become more conservative? Implications for capital structure and debt pricing. *The Journal of Finance, 69*(5), 1961–2005.

Barrot, J. N., & Sauvagnat, J. (2016). Input specificity and the propagation of idiosyncratic shocks in production networks. *The Quarterly Journal of Economics, 131*(3), 1543–1592.

Bates, T. W., Kahle, K. M., & Stulz, R. M. (2009). Why do US firms hold so much more cash than they used to? *The Journal of Finance, 64*(5), 1985–2021.

Beaver, W. H., Shakespeare, C., & Soliman, M. T. (2006). Differential properties in the ratings of certified versus non-certified bond-rating agencies. *Journal of Accounting and Economics, 42*(3), 303–334.

Becker, B., & Milbourn, T. (2011). How did increased competition affect credit ratings? *Journal of Financial Economics, 101*(3), 493–514.

Bernile, G., Bhagwat, V., & Rau, P. R. (2017). What 'doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior. *The Journal of Finance, 72*(1), 167–206.

Bharath, S. T., & Shumway, T. (2008). Forecasting default with the Merton distance to default model. *The Review of Financial Studies, 21*(3), 1339–1369.

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics, 142*(2), 517–549.

Bonsall, S. B., IV, Holzman, E. R., & Miller, B. P. (2017). Managerial ability and credit risk assessment. *Management Science, 63*(5), 1425–1449.

Boone, A. L., & White, J. T. (2015). The effect of institutional ownership on firm transparency and information production. *Journal of Financial Economics, 117*(3), 508–533.

Brogaard, J., Li, D., & Xia, Y. (2017). Stock liquidity and default risk. *Journal of Financial Economics, 124*(3), 486–502.

Brown, J. R., Gustafson, M. T., & Ivanov, I. T. (2021). Weathering cash flow shocks. *The Journal of Finance, 76*(4), 1731–1772.

Cameron, A. C., Gelbach, J. B., & Miller, D. L. (2011). Robust inference with multiway clustering. *Journal of Business & Economic Statistics, 29*(2), 238–249.

Cevik, S., & Jalles, J. T. (2023). Feeling the heat: Climate shocks and credit ratings. *Review of Development Finance, 13*(2), 21–34.

Chava, S. (2014). Environmental externalities and cost of capital. *Management Science, 60*(9), 2223–2247.

Chavaz, M. (2016). Staff working paper no. 617 dis-integrating credit markets: Diversification, securitization, and lending in a recovery. In *Bank of England. Staff Working Paper No. 617*.

Chemmanur, T. J., Karagodsky, I., & Toscano, F. (2020). *Incentives, clienteles, and information production: New evidence from investor-paid and issuer-paid agency credit ratings and equity analyst recommendations. Working Paper*. Boston College.

Cheng, M., & Subramanyam, K. R. (2008). Analyst following and credit ratings. *Contemporary Accounting Research, 25*(4), 1007–1044.

Cohn, J. B., Liu, Z., & Wardlaw, M. I. (2022). Count (and count-like) data in finance. *Journal of Financial Economics, 146*(2), 529–551.

Cornaggia, J., & Cornaggia, K. J. (2013). Estimating the costs of issuer-paid credit ratings. *The Review of Financial Studies, 26*(9), 2229–2269.

Cornaggia, K. J., Krishnan, G. V., & Wang, C. (2017). Managerial ability and credit ratings. *Contemporary Accounting Research, 34*(4), 2094–2122.

Cortés, K. R., & Strahan, P. E. (2017). Tracing out capital flows: How financially integrated banks respond to natural disasters. *Journal of Financial Economics, 125*(1), 182–199.

Djankov, S., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2008). The law and economics of self-dealing. *Journal of Financial Economics, 88*(3), 430–465.

Driss, H., Drobetz, W., El Ghoul, S., & Guedhami, O. (2021). Institutional investment horizons, corporate governance, and credit ratings: International evidence. *Journal of Corporate Finance, 67*, Article 101874.

Duan, J. C., Sun, J., & Wang, T. (2012). Multiperiod corporate default prediction—A forward intensity approach. *Journal of Econometrics, 170*(1), 191–209.

Elyasiani, E., Jia, J. J., & Mao, C. X. (2010). Institutional ownership stability and the cost of debt. *Journal of Financial Markets, 13*(4), 475–500.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., & Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies, 33*(3), 1184–1216.

Faulkender, M., & Petersen, M. A. (2006). Does the source of capital affect capital structure? *The Review of Financial Studies, 19*(1), 45–79.

Fitch Ratings. (2023). *Special report: Incorporating climate change into credit ratings*. Fitch Ratings. February 2023 https://www.fitchratings.com/research/corporate-finance/climate-vulnerability-in-corporate-ratings-discussion-paper-15-02-2023.

Frost, C. A. (2007). Credit rating agencies in capital markets: A review of research evidence on selected criticisms of the agencies. *Journal of Accounting, Auditing & Finance, 22*(3), 469–492.

Galil, K., Shapir, O. M., Amiram, D., & Ben-Zion, U. (2014). The determinants of CDS spreads. *Journal of Banking & Finance, 41*, 271–282.

Gow, I. D., Ormazabal, G., & Taylor, D. J. (2010). Correcting for cross-sectional and time-series dependence in accounting research. *The Accounting Review, 85*(2), 483–512.

Graham, J. R., & Harvey, C. R. (2001). The theory and practice of corporate finance: Evidence from the field. *Journal of Financial Economics, 60*(2–3), 187–243.

Grunert, J., Norden, L., & Weber, M. (2005). The role of non-financial factors in internal credit ratings. *Journal of Banking & Finance, 29*(2), 509–531.

Hand, J. R., Holthausen, R. W., & Leftwich, R. W. (1992). The effect of bond rating agency announcements on bond and stock prices. *The Journal of Finance, 47*(2), 733–752.

Harford, J., Klasa, S., & Maxwell, W. F. (2014). Refinancing risk and cash holdings. *The Journal of Finance, 69*(3), 975–1012.

Hung, M., Kraft, P., Wang, S., & Yu, G. (2022). Market power and credit rating standards: Global evidence. *Journal of Accounting and Economics, 73*(2–3), Article 101474.

Huynh, T. D., & Xia, Y. (2021). Climate change news risk and corporate bond returns. *Journal of Financial and Quantitative Analysis, 56*(6), 1985–2009.

Kisgen, D. J. (2006). Credit ratings and capital structure. *The Journal of Finance, 61*(3), 1035–1072.

Kisgen, D. J. (2007). The influence of credit ratings on corporate capital structure decisions. *Journal of Applied Corporate Finance, 19*(3), 65–73.

Kisgen, D. J., & Strahan, P. E. (2010). Do regulations based on credit ratings affect a firm's cost of capital? *The Review of Financial Studies, 23*(12), 4324–4347.

Kliger, D., & Sarig, O. (2000). The information value of bond ratings. *The Journal of Finance, 55*(6), 2879–2902.

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies, 33*(3), 1067–1111.

Kuang, Y. F., & Qin, B. (2013). Credit ratings and CEO risk-taking incentives. *Contemporary Accounting Research, 30*(4), 1524–1559.

La Porta, R., Lopez-de-Silanes, F., Shleifer, A., & Vishny, R. W. (1997). Legal determinants of external finance. *The Journal of Finance, 52*(3), 1131–1150.

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature, 529*(7584), 84–87.

Li, F., Lin, C., & Lin, T. C. (2022). *A one-two punch to the economy: Climate change vulnerability and corporate innovation. Working Paper*. University of Hong Kong.

Liberti, J. M., & Petersen, M. A. (2019). Information: Hard and soft. *The Review of Corporate Finance Studies, 8*(1), 1–41.

Ma, Z., Ruan, L., Wang, D., & Zhang, H. (2021). Generalist CEOs and credit ratings. *Contemporary Accounting Research, 38*(2), 1009–1036.

Massa, M., & Zhang, L. (2021). The spillover effects of hurricane Katrina on corporate bonds and the choice between bank and bond financing. *Journal of Financial and Quantitative Analysis, 56*(3), 885–913.

McLean, R. D. (2011). Share issuance and cash savings. *Journal of Financial Economics, 99*(3), 693–715.
Merton, R. C. (1974). On the pricing of corporate debt: The risk structure of interest rates. *The Journal of Finance, 29*(2), 449–470.
Nordhaus, W. (2019). Climate change: The ultimate challenge for economics. *The American Economic Review, 109*(6), 1991–2014.
Opler, T., Pinkowitz, L., Stulz, R., & Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of Financial Economics, 52*(1), 3–46.
Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies, 22*(1), 435–480.
Pham, M. H., Merkoulova, Y., & Veld, C. (2023). Credit risk assessment and executives' legal expertise. *The Review of Accounting Studies*, 1–40.
Safiullah, M., Kabir, M. N., & Miah, M. D. (2021). Carbon emissions and credit ratings. *Energy Economics, 100*, Article 105330.
Sautner, Z., van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance, 78*(3), 1449–1498.
Schüwer, U., Lambert, C., & Noth, F. (2019). How do banks react to catastrophic events? Evidence from Hurricane Katrina. *The Review of Finance, 23*(1), 75–116.
Seltzer, L. H., Starks, L., & Zhu, Q. (2022). *Climate regulatory risk and corporate bonds (No. w29994)*. National Bureau of Economic Research (NBER) Working Paper.
Standard & Poor''s. (2002). *Understanding credit ratings. January 1–4*.
Xia, H. (2014). Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies? *Journal of Financial Economics, 111*(2), 450–468.