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Climate Change Exposure and Cost of Equity

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Abstract

In this study, we investigate the association between climate change exposure and the cost of equity financing. Using a novel dataset of US firm-level exposure to climate change risks, we find that higher exposure to climate risks co-exists with higher financing costs for the period 2010 through 2021. While the effect of physical and regulatory risks is rather muted, the main mechanism shaping financing costs stems from climate transition risk driven by uncertainty about new business opportunities. Our results are not compromised by endogeneity concerns as shown by alternative methods such as entropy balancing, instrumental variable regression, dynamic panel estimation and a difference-in-differences setting. We also document that the link between climate change exposure and the cost of equity financing is more prominent for firms facing higher attention to climate topics, a stronger realization of climate change and more problematic financing constraints.

JEL Codes: G12, G14, G32, Q54

Keywords: Climate Change, Cost of Equity, Transition Risk, Market Discipline

1. Introduction and Related Literature

As the shift in global warming becomes increasingly discernible, its economic and financial implications have garnered significant attention. The transformative change in climate patterns has not only led to environmental repercussions but has also begun to echo in the world of finance and investment. Businesses worldwide, from various industries, are grappling with the direct and indirect effects of climate change, including operational disruptions, regulatory constraints, and market fluctuations (Heo, 2021). In particular, it is now essential to understand the economic impacts of climate change, specifically in relation to firm financing. Companies across industries and regions are increasingly recognizing climate change as a critical strategic issue that could affect their business models and overall viability. With the escalation of climate-related risks, companies face increasing pressure from stakeholders, including investors, regulators, customers, and the public, to incorporate climate considerations into their strategic planning, risk management, and disclosure practices. These challenges are particularly pronounced in the context of financing, as the capital markets have started to factor in climate risks into their pricing and allocation decisions (Bolton and Kacperczyk, 2021).

The accelerated pace of climate change and its multifarious consequences are emerging as a subject of paramount interest for researchers, policymakers, and investors alike. Concurrently, it has stimulated a surge of literature examining its impacts on different facets of business and economics. Firms' strategic and financial behavior in the face of climate change has been a growing area of focus, with a consensus emerging that climate change exposure significantly affects firms' financial decisions and performance. The implications of climate change exposure are diverse, with consequences ranging from increased cash holdings (Heo, 2021) and revised downside risk dynamics (Chen et al., 2023) to increased spreads on bank loans (Javadi and Masum, 2021) and a higher premium on mortgage credits (Nguyen et al., 2022). Notably, Kling et al. (2021) provide a comprehensive investigation of how climate vulnerability affects firms' cost of capital and access to finance. They reveal a direct and indirect effect of climate vulnerability on cost of debt, although no significant evidence is found on its impact on cost of equity.[1]

Building on these insights, our study aims to directly tackle the association between climate change exposure and the cost of equity financing. We intend to address this gap by using a novel dataset of firm-level exposure to climate risks in the US, constructed by Sautner et al. (2023) through a detailed processing of earnings call transcripts. This dataset provides an opportunity to empirically quantify how different types of climate risks, including physical risks, regulatory risks, and transition risks, interact with companies' operations.

By way of preview, our baseline findings reveal that climate change exposure brings a statistically and economically significant elevation in the cost of equity financing. In contrast to the other sub-components of climate change exposure including regulatory and physical shocks, the uncertainty emerging from opportunity shocks (relevant to the transition risks of global warming) is significantly associated with the increase in funding costs faced by firms in the capital markets. To handle potential endogeneity concerns, we perform a myriad of alternative estimations and empirical designs. The collective findings from: entropy balancing analysis; instrumental variable approach; dynamic panel estimation; and difference-in-differences exercise validate the baseline inferences. Moreover, we show that baseline findings are invariant against a variety of robustness checks including: different ways to construct

[1] Furthermore, the literature establishes that public attention and regulation also play critical roles in how climate risk impacts business operations. Chen et al. (2023) explore the role of public climate attention in increasing downside risk, particularly for high-carbon-emission firms. Trinks et al. (2022) demonstrate how the transition from high- to lower-carbon production systems can lead to regulatory and market risks for high-emitting firms, which in turn may require investors to demand an equity premium. These studies underscore the broader societal and regulatory context in which firms operate and their impact on the firms' financial positions.

standard errors; alternative dependent variable; restricted sample coverage; and additional controls. Our extended set of estimations also explores potential channels as we find that the effect on the cost of equity financing is amplified for firms operating under higher awareness for and intensity of climate change risks as well as the firms with a higher likelihood of bankruptcy and financial constraints.

Our paper contributes to the climate finance literature by offering new insights. While some studies examine the cost of equity capital in the context of greenhouse gas emissions or climate vulnerability (Kim et al., 2015; Kling et al., 2021; Trinks et al., 2022), a detailed examination of how firms' overall climate change exposure relates to their cost of equity financing has not been conducted. Hence, our study addresses this gap by utilizing a novel dataset of US firm-level exposure to climate change risks constructed by Sautner et al. (2023). In contrast to previous studies that focus on single aspects of climate risk, our study offers a more comprehensive analysis, considering various climate risks in conjunction with one another (e.g., physical, regulatory, or transition risks). While Javadi and Masum (2021) underscore the role of climate risk in determining the cost of borrowing, and Kim et al. (2015) emphasize the influence of carbon intensity on the cost of equity capital, our study goes a step further to illustrate that the impact of climate risks on the cost of equity financing is contingent on factors such as public attention to climate issues, the realization of climate change, and the severity of financing constraints a firm encounters. Additionally, by employing advanced alternative methods, we effectively address and mitigate potential endogeneity concerns.

Overall, our study contributes to the literature that explores the potential benefits of sustainability for firms' financial health (Ferrell et al., 2016; Lins et al., 2017). We try to provide an essential perspective to the debate on climate finance and sustainability, while enriching the knowledge base that academics, policymakers, and business leaders can draw upon when navigating the intricate intersections between climate change, firm-level decisions, and financial markets.

The rest of the paper is formulated as follows. Section 2 provides details about data sources, Section 3 describes the methodological approach, Section 4 presents empirical findings, and Section 5 concludes the paper.

2. Data

Our sample spans the interval between 2010 and 2021. The beginning of the sample period is chosen to exclude the distortions caused by the Global Financial Crisis on the pricing behavior in equity markets, whereas the end of the sample is marked with the data availability of the climate change exposure index. We obtain daily stock price data required to estimate the cost of equity from CRSP, augmented by the additional data downloaded from Aswath Damodaran's webpage. This data is later matched with the annual Compustat data set to retrieve firm fundamentals, state-of-(headquarters') location as well as the balance sheet and income statement items.

In the following step, we merge US firms' stock price and financial data with the climate change exposure index by using the data set made available by Sautner et al. (2023). We use the permanent firm identifier (GVKEY) to establish this link. We omit the firms corresponding to missing key financial statement items such as total assets and equity. Our ultimate sample is composed of an unbalanced panel of 1,238 unique firms with 8,749 firm-year observations. The resultant sample is representative based on broad sectoral coverage (following Global Industry Classification-GIC standards) ranging from energy to industrials, from utilities to information technology.

For our extended estimations, we make use of state-level supplementary data sets including voting patterns for US Senate elections taken from MIT Election Data and Science Lab, climate attention index constructed via Bloomberg Terminal, abnormal temperature and extreme weather events collected from National Oceanic and Atmospheric Administration (NOAA) and Universal Ecological Fund.

3. Methodology

Our empirical design consists of two steps. We first attempt to estimate the cost of equity financing by following the conventional Capital Asset Pricing Model (CAPM) and then try to associate firms' climate change exposure with funding costs. The specification to estimate the cost of equity is as follows:

$$CoE_{it} = RF_t + (\beta_{it})ERP_t \tag{1}$$

where CoE stands for the cost of equity of firm i in year t, RF denotes risk-free rate in the form of yield on 3-months T-bill and ERP represents the implied equity risk premium calculated and made publicly available by Aswath Damodaran (based on a simple two-step augmented dividend discount model). The parameter indicating systematic risk, β, is generated by implementing firm-level rolling window regressions of daily logarithmic stock returns to daily returns on the market index (S&P 500).

The second step involves the following specification to assess whether climate change exposure commands a premium in the cost of equity capital:

$$CoE_{it} = \gamma CC\_Exposure_{it-1} + \vartheta X_{it-1} + \delta_i + \theta_t + \varepsilon_{it} \tag{2}$$

where CoE is the cost of equity series calculated in Equation (1). The main variable of interest is $CC\_Exposure$ defined as the natural logarithm of one plus firm-level climate change exposure index generated by Sautner et al. (2023). The index is lagged by one period to account for potential simultaneity bias. Equation (2) incorporates unobserved firm heterogeneities with firm fixed effects (δ_i) and time-varying (macroeconomic, regulatory, social and financial market-related) aggregate factors influencing all firms' equity financing costs simultaneously with year fixed effects (θ_t). ε_{it} refers to the stochastic error term. We cluster the standard errors at the GIC industry level (6-digit) to account for the potential correlations across firms within the same industry.

Following the prior literature, we also include a wide range of firm controls that could potentially affect the cost of equity financing. As a predictor of firms' mispricing relative to the fundamental value, $Book - to - Market$ is defined as the book value of equity divided by the market value of equity (Fama and French, 2015; Balakrishnan et al., 2021). As a common way to proxy firm size in the finance literature, we construct the natural logarithm of total assets ($Firm\ Size$). Larger firm size can enhance the information availability and decrease the cost of external financing (Gebhardt et al., 2001; Francis et al., 2005), or the position on the corporate life-cycle can elevate the cost of equity, especially for the young and immature firms with uncertain income prospects and lower retained earnings (Hasan et al., 2015). Alternatively, due to the wider scope of operations and business processes, larger firms may be prone to a higher likelihood of reputational problems, internal control deficiencies and corporate misconduct which can be reflected in the risk assessment of market participants resulting in a higher cost of external financing (Cao et al., 2015; Nicholls, 2016). To capture the impact of profitability (Fama and French, 2006), we create the net income to total sales (NPM) and operating income to total assets (ROA) proxies. The financial sustainability of firms (measured by generated profits) is expected to correlate negatively with the cost of equity (Ng and Rezaee, 2015). Beginning with the seminal contribution of Modigliani and Miller (1958), the existing literature establishes that the cost of equity increases with the firm leverage (Dhaliwal et al., 2006). We control for this firm dimension by using the ratio of total liabilities to total assets ($Leverage$). As the last control variable, we use the ratio of research & development expenditures to total sales ($R\&D$). All continuous variables are winsorized at 1st and 99th percentiles to overcome the effect of outliers. Variable definitions and summary statistics are presented in Tables 1 and 2.

The main coefficient of interest, γ, (attached to $CC\_Exposure$) gauges the extent to which climate change exposure affects the cost of equity capital. Sautner et al. (2023) construct a novel proxy for firm-level exposure to climate change by implementing machine learning techniques to analyze the corpus of earnings call transcripts. In this context, the time-varying indicator is created by measuring the relative frequency with which climate-related bigrams (pre-determined set of word/phrase combinations) appear in the call transcripts normalized by the total number of bigrams occurring in the transcripts. Higher values of $CC\_Exposure$ demonstrate that firms are more exposed to the overall risks arising from climate change as well as different sub-components involving opportunity shocks, regulatory shocks and physical shocks.

In contrast to the other means of corporate communication tools (such as annual reports, CSR reports and press releases) which can be plagued with greenwashing and window dressing regarding how firm operations contribute to or are influenced by climate change, earnings calls enable analysts, investors and other stakeholders to truly grasp executives' views and policy agenda by also allowing them to raise questions during the calls (Hollander et al., 2010; Eccles and Serafeim, 2013). Additionally, the widely preferred "hard" indicators (such as carbon emissions and pollution) employed by the recently emerging literature to investigate climate-related topics in the context of corporate finance are only available for a subset of the entire firm universe depending on the fact that firms opt to disclose data, while such measures are generally backward-looking (Hossain et al., 2022; Nguyen et al., 2023). Jiang et al. (2023) show that earnings call events represent an important source of outside monitoring for climate concerns by documenting that the decreasing number of environment-related questions directed by participants during conference calls contributes to firm-level pollution. Sautner et al. (2023) also find that the measure constructed through earnings calls successfully predicts real-life outcomes governing climate change mitigation such as green-tech jobs and green patents.

[**Insert Table 1 Here**]

[**Insert Table 2 Here**]

4. Empirical Results

This section discusses the empirical findings by presenting the main results first, followed by additional analyses to alleviate endogeneity concerns, to perform robustness checks and to explore potential channels driving the association between climate change exposure and financing costs.

4.1. Baseline Results

Our baseline findings are presented in Table 3. In column (1), we estimate the parsimonious specification without any firm-level controls, whereas column (2) considers the saturated one comprising the firm-level controls together with firm and year fixed effects. In both cases, the coefficient on $CC\_Exposure$ enters the regressions positively and significantly (at a 1% significance level). This shows that firms' external equity financing costs elevate in tandem with their exposure to climate change risks. Our inference aligns with earlier studies such as Painter (2020) who discovers an increase in underwriting fees and yields for climate risk-prone areas, and Huynh and Xia (2020), who find that climate risk news is factored into bond returns. Furthermore, Delis et al. (2020) and Seltzer et al. (2022) provide evidence that climate risk is priced in loan spreads and credit ratings, respectively, suggesting a similar elevation in cost for firms with higher climate change exposure.

Nevertheless, as noted by Sautner et al. (2023), the distributional features of $CC\_Exposure$, such as being a count-based measure and having a large mass of values at zero together with potentially problematic skewness, may render the OLS estimation method unreliable. Therefore, in columns (3) and (4), we utilize Poisson regressions for similar specifications with and without controls. The sign and significance of the main coefficient remain qualitatively similar still highlighting the positive association between climate risks and financing costs.

The effect is also economically relevant. As a commonly used standardized measure (Mitton, 2022), we multiply the coefficient attached to $CC\_Exposure$ (based on column (2) of Table 3) with its standard deviation scaled by the standard deviation of the outcome variable (CoE) following the concept of beta regression. We find that the effect is economically significant as such a one standard deviation change in climate change exposure implies a 5.6% standard deviation increase in the cost of equity.

Turning our attention to other controls, we observe that estimated relationships are mostly in line with other works and prior literature. Firms with higher $Book-to-Market$ values enjoy lower financing costs. $Firm\ Size$ emerges as a significant predictor of the cost of equity. More profitable firms with higher NPM and ROA experience lower external financing costs, whereas $Leverage$ is positively correlated with the outcome variable.

[**Insert Table 3 Here**]

Having established that the vulnerabilities arising from climate change command an incremental premium for the cost borne by firms to raise additional equity, we investigate the sources of this risk through sub-components of $CC\_Exposure$. In their examination of earnings call transcripts, Sautner et al. (2023) also process bigrams specifically describing different dimensions of climate change exposure given that the effects on individual firms tend to be multi-faceted (Giglio et al., 2021). The first shock category captures the opportunities ($CC\_Exposure\_Opp$) presented to firms given global warming and accompanying technological change, whereas the second and third shock categories track regulatory risks ($CC\_Exposure\_Rg$) and physical threats ($CC\_Exposure\_Ph$) due to climate change, respectively. When we replace the outcome variable with these sub-components and apply both OLS and Poisson estimators, in Table 4, we observe that the effect is highly significant for $CC\_Exposure\_Opp$.

This finding is somewhat intuitive considering that new investment and business opportunities initiated thanks to climate change (to exemplify, solar or battery technologies) may create considerable gains and returns for the shareholders if implemented successfully but can cause considerable losses in case of unsuccessful implementation. It can be attributed to the fact that several elements potentially impacting a company's capacity to transition towards a more environmentally friendly economy also possess significant components at the company level, such as managerial competence, innovation, or financial limitations (Sautner et al., 2023). Thus, the incidental uncertainty on firm profitability may be translated into higher risk assessments and equity risk premium. Moreover, our results support the insight that the effect is mostly driven by transition risks arising from the firms' (and in a broader sense society's) response to mitigate the consequences of climate change by transitioning to a lower-carbon economy instead of the more direct channel via physical risk corresponding to the inability of physical assets to generate revenue in case of damage caused by global warming (Benedetti et al., 2021; Semieniuk et al., 2021; Huang et al., 2021; Apel et al., 2023).

[**Insert Table 4 Here**]

4.2. Endogeneity Concerns

In this section, we present additional analyses conducted to further alleviate potential endogeneity concerns surrounding baseline estimations (Table 5).

[**Insert Table 5 Here**]

It is expected that firms with higher and lower sensitivities to climate change exposure also differ in other observable characteristics. The incapability of the baseline regression model to account for such systematic differences and covariate imbalance can complicate the inference process. In this context, we follow the novel approach of entropy balancing which is a re-weighting scheme applied to the pre-processing of units in a binary treatment observational study with the intent that the moments of covariate distributions are identical across treatment and re-weighted control group. This method presents particular benefits over the traditional matching procedures used to alleviate systematic observable differences between treatment and control observations (Hainmueller, 2012; Hainmueller and Xu, 2013; Zhao and Percival, 2017; McMullin and Schonberger, 2020).[2] In this context, we first disentangle the sample firms into two groups based on the median threshold value of $CC\_Exposure$, and then we utilize the set of firm controls and balancing constraints of the first moment to determine the weights. In the

[2] Entropy balancing preserves all observations, thus maintaining vital details about the whole sample. This method naturally produces an ideal balance of covariates by leveraging the properties of the distribution. Additionally, this process is not swayed by the researcher's choice of the ancillary empirical model to forecast the allocation of observations to the treatment cluster. The entropy balancing methodology demonstrates considerable adaptability, and its supremacy over alternative matching techniques has been corroborated by previous simulation-based research.

subsequent step, we re-run the baseline model using the weighted sample observations. In column (1) of Table 5, we show that $CC\_Exposure$ still has a positive coefficient with statistical significance at the 5% conventional level.

Another common method to cope with endogeneity problems (and establish causality) in empirical finance is instrument variable (IV) estimation (Roberts and Whited, 2013). To construct a valid instrument, we create the variable $CC\_Exposure\_Sector$ which is the time-varying average of climate change exposure at the sectoral level (2-digit GIC classification). Arguably, this instrument satisfies the relevance condition in the sense that we expect a higher degree of correlation between firm-level exposure to climate risks and overall climate risk faced by the sector to which a particular firm belongs to. For instance, firms mainly operating in the energy or utilities sectors are expectedly more prone to transition risks driven by global warming due to their asset structure, business processes, suppliers, and consumer base. Similarly, sectoral climate exposure should affect a particular firm's financing costs only through that particular firm's climate change exposure and given the non-existence of monopolies in the US setting, it is very unlikely that a specific firm's climate exposure determines the overall sector exposure. These qualitative properties imply that our instrument should satisfy the "only-through" condition, exogeneity requirement and exclusion restriction. Prior literature also often adopts a similar approach when instrumenting the environmental, social and governance (ESG) performance of individual firms (Bouslah et al., 2018; Aouadi and Marsat, 2018). Our IV estimation involves a two-step procedure where the first stage entails regressing the main independent variable ($CC\_Exposure$) on the instrument ($CC\_Exposure\_Sector$) whereas the second stage uses the fitted values from this estimation ($CC\_Exposure\_Fitted$) to replace the independent variable in order to test the relationship between climate risks and the cost of equity. In column (2), it is seen that the relevance condition is formally satisfied as $CC\_Exposure\_Sector$ has a significant and positive coefficient in predicting firm-level $CC\_Exposure$. In column (3), we see that instrumented $CC\_Exposure$ is still positively and significantly related to the cost of equity financing. We also perform the necessary instrument relevance diagnostics tests for the validity of the IV estimation. The Kleibergen-Paap rk LM test statistic is significant at a 5% level affirming that the null hypothesis of model under-identification (excluded instruments are correlated with endogenous regressor) can be rejected. Furthermore, we employ the Kleibergen-Paap Wald rk F statistic which stays above the Stock-Yogo critical value (at 10%) rejecting the null hypothesis that excluded instruments are weak.

As the next method to limit endogeneity concerns, we opt to run dynamic panel estimation with the system generalized method of moments (GMM) (Arrelano and Bover, 1995; Blundell and Bond, 1998; Roodman, 2009). Apart from handling the endogeneity of the main variable of interest ($CC\_Exposure$), this technique can also account for potential persistence in the cost of equity by appending the baseline specification with the lags of the outcome variable. To this end, we add $CC\_Exposure(t-1)$ and $CC\_Exposure(t-2)$ to our empirical model. As suspected, the estimation results given in column (4) of Table 5 indicate that lagged outcome variable terms are positive and significant. More importantly, GMM estimates for $CC\_Exposure$ remains positive and significant confirming the baseline findings after neutralizing the endogeneity problems. The appropriateness of instrumentation is shown via the Hansen test statistic failing to reject the null hypothesis that the overidentifying restrictions are valid.[3]

[3] In this case, we limit the number of lags for instrumentation of endogenous variables with two and three to ensure the applicability of the rule of thumb which states that the number of instruments should be lower than the number of firms. However, unreported results with alternative instrument lag choices yield that our inferences stay similar.

To further immune our findings from endogeneity, we make use of a quasi-experimental design exploiting an exogenous shift in the relative importance attached to climate change exposure of US firms during our sample period. In 2017, following the initial announcement by President Donald Trump, the US administration submitted an official notice to the United Nations declaring the intention to withdraw from the Paris Agreement which had been signed in 2015. This agreement represented a milestone global climate deal as such countries responsible for 97% of the global greenhouse emissions agreed to address global warming by maintaining the rise in average global temperature below 2°C (relative to the pre-industrial level) and more preferably limiting the increase to 1.5°C (Falkner, 2016; Scheussner et al., 201; Reghezza et al., 2022). Prior works have shown that the withdrawal decision had material impacts on firms through climate change mitigation efforts and risk perceptions. Nong and Siriwardana (2018) forecast that the proposed withdrawal would allow US energy firms (as a heavily vulnerable industry group to climate change initiatives) to expand operations. Liu et al. (2020) argue that the withdrawal from the agreement does not create long-term welfare benefits for the departing countries. Seltzer et al. (2022) document that wider corporate bond spreads and lower credit ratings assigned to polluting US firms reversed after the withdrawal announcements on the back of expectations concerning looser climate regulations.

Considering the exogenous nature of this withdrawal (not driven by firm-level policies or characteristics but introduced as a part of broader political agenda) in shaping the climate mitigating regulatory efforts and perceptions against climate risks, following the other studies such as Klaus et al. (2022), we employ the withdrawal process in a difference-in-differences (DiD) setting. To this end, we first rank the sample firms based on the $CC\_Exposure$ scores as of 2017 and define a binary indicator describing the treatment group ($High\ Exposure$) taking the value of one for the firms with higher than median climate change exposure index score, otherwise zero for the control group. Then, we describe the treatment timing by constructing $Paris\ Withdrawal$ variable taking the value of one for the period between 2018-2020 and the value of zero for the interval 2015-2017. This event window aims to exclude the pre-Paris Agreement period and to form a symmetric time coverage across the withdrawal decision. In column (5) of Table 5, we estimate the simple DiD model where the coefficient attached to interaction term $Paris\ Withdrawal$ x $High\ Exposure$ assesses how the financing costs of high climate change exposure firms evolve from pre- to post-withdrawal period relative to firms with lower climate change exposure. The coefficient is found to be negative and significant implying that loosening scrutiny (concerning environmental risks) decreases the cost of raising external equity financing for firms with considerable exposure to climate change. In untabulated set of results, we implement two different tests to enhance the validity of the DiD exercise. In the first test, we restrict the sub-sample to 2016-2019 (by keeping the treatment timing the same) and obtain very similar results. In the second test, we select an entirely different sample period covering the interval of 2010-2015 and define a pseudo $Paris\ Withdrawal$ taking the value of one from 2013 onwards. As expected, this placebo estimation turns out to be insignificant.

In the last step, we undertake a formal test of whether our results are driven by the omitted variable bias. We employ the testing procedure introduced by Oster (2019) evaluating the persistence of regression coefficients with and without other control variables based on the idea that the selection on observables is proportional to the selection on unobservables. By also using the R-squared values from parsimonious and saturated regression specifications, this test constructs an identifiable interval for the coefficient of interest offering upper and lower bounds for bias. If this interval does not contain zero, then the hypothesis that the findings are seriously driven by omitted variables can be rejected. The identified interval is constructed as $[\tilde{\gamma}, {\gamma^*}']$

where $\gamma^{*\prime} = \tilde{\beta} - \partial[\dot{\gamma} - \tilde{\gamma}]\frac{R_{max} - \tilde{R}}{\tilde{R} - \dot{R}}$. In this specification, $\tilde{\gamma}$ and $\tilde{R}$ are coefficient estimate and R-squared values from the baseline model inclusive of all the observed control variables, whereas $\dot{\gamma}$ and $\dot{R}$ stand for the same values derived from without any control variables. We follow the suggestions of Oster (2019) and Mian and Sufi (2014) to determine the parameters $\partial = 1$ and $R_{max} = \min(2.2\tilde{R}, 1)$, respectively. As a result of this investigation, the aforementioned set excludes the zero threshold and further validates our results.

4.3. Robustness Checks

In this part, we revert to the specification in Equation (2) and aim to reinforce the robustness of the baseline relationship between climate change exposure and the cost of equity. For the sake of brevity, robustness checks for the coefficient ($CC\_Exposure$) obtained in column (2) of Table 3 are presented in the rows of Table 6.

[**Insert Table 6 Here**]

We follow alternative choices for standard error clustering in rows (1) and (2). In the former case, two-way clustering is performed (industry and year), whereas the latter case cluster the errors at the more restrictive firm level by evidently preserving the statistical significance in both cases. In row (3), we replace the dependent variable CoE with the raw $Beta$ measure shown in Equation (1). Estimation results continue to indicate that climate change exposure introduces additional systematic risk in stock returns. Row (4) restricts the sample by dropping all observations after 2019. Row (5) appends Equation (2) by including other firm-level controls such as price-to-earnings ratio (P/E), multiple of enterprise value to EBITDA (EVM), cash-to-total liabilities ratio ($Cash$) and capital expenditures to total assets ratio ($CAPEX$). These sensitivity analyses keep showing that climate risks are considered by market participants in evaluating firms. In row (6), instead of year fixed effects, we control for higher degree industry-by-year fixed effects. Although our sample predominantly consists of non-financial firms, in row (7), we omit a few publicly traded financial companies from the sample and repeat the estimations. We still demonstrate the positive association between climate change exposure and financing costs.

Considering that investors' reactions to the shift in firm-level climate exposure outlook can be transmitted rather quickly, we run the baseline regression by taking the contemporaneous value of $CC\_Exposure$ instead of lagged values. In row (9), to ensure the reader that our results are not driven by the mass $CC\_Exposure$ values concentrating on zero threshold, we repeat the estimations by deleting all such observations from the sample. We reiterate that our baseline findings are not contingent on modeling choices. Given that the discussion in earnings calls is mostly initiated by stock analysts and institutional investors, we anticipate that the assessments of firms' climate change exposure should mainly be reflected in the cost of equity form of financing. Thus, we designate a placebo analysis where we replace the outcome variable with an indicator proxying to the cost of debt financing. At this point, we create the variable CoD defined as the ratio of interest expenses to total debt, subsequently used as the outcome variable. As expected, in row (10), we detect that the effect of climate change exposure on this indicator of an alternative form of financing is insignificant. In row (11), we only keep the firms with 5 years of consecutive observations to ensure that our results are not spuriously driven by survivorship bias or data availability. Lastly, in row (12), we plan to neutralize the effect of the variation in firms' existing organizational policies and procedures designed to address climate concerns. To do this, we append our original sample data with the firm-level environmental performance score retrieved from the Thomson Reuters database. When we expand the set of controls with the environmental pillar of the Refinitiv ESG score ($E - Score$), our results continue to hold.

4.4. Underlying Mechanisms

Next, we investigate the cross-sectional heterogeneity in the effect of climate change exposure on the cost of financing to better understand the underlying mechanisms (Table 7).

[**Insert Table 7 Here**]

The first dimension we consider is the level of attention given to the consequences of climate change. Undeniably, there has been an overall change in public opinion about the negative externalities of climate change over the last decade (Egan et al., 2022). However, there are still considerable variations in attitudes toward risk perceptions about climate change, concerns about its consequences and demand for policy response depending on demographic, societal and political characteristics. The opinion on (and relatedly the importance given to) global warming had been heavily polarized in the US due to partisan and ideological background (Guber, 2013). The opposition to a transition from a fossil fuel-dependent economic orientation to a more sustainable one is mainly observed among economic conservatives (Egan and Mullin, 2017; Thomas et al., 2022). Howe et al. (2015) empirically document that public attention to global warming is shaped by the geographic diversity in the political environments for climate policy. The existing literature overwhelmingly shows that attention to climate issues alters the pricing (and volatility) of assets in: housing markets (Baldauf et al., 2020); bond markets (Painter et al., 2020); and equity markets (Chen et al., 2023). In this context, we use two indicators with spatial variation to separate the sample into sub-groups where individual firms operate across the markets with high and low degrees of attention to climate change. We use firms' state-of-location to match market characteristics with the original sample. The division of the sample in column (1) of Table 7 is done in line with the variable $Democrat$ such that firms located in a state in which the proportion of constituent votes for the Democrat Party (in the US Senate elections) exceeds the sample median threshold, whilst column (2) includes the firms situated in a state with a lower degree of inclination to vote for Democrat Party. We find that the role of climate change exposure in commanding a equity risk premium is stronger across states with potentially more awareness for climate issues. To complement this analysis, we collect $Climate\ Attention\ Index$ (from Bloomberg) which is a continuous measure of state-level media coverage on climate change topics developed by the annual sum of daily news counts regarding climate change themes. Column (3) considers only the firms located in a state with higher than median value of $Climate\ Attention\ Index$, whereas column (4) retains the firms operating in a state with lower than median value. Our findings still show that the effect is larger and significant for firms facing more attention to climate policies.

As the second dimension, we focus on the severity of climate change with potential impacts on how investors assess company risks. Personal experiences and damage due to climate abnormalities such as unusual temperature shifts as well as severe rains, flooding, drought and hurricanes can heighten climate concerns on a temporary basis (Konisky et al., 2016; Sisco et al., 2017). The term coined as local warming is likely to reinforce individuals' beliefs about global climate change itself (Zaval et al., 2014). Market participants reflect the severity aspect of climate exposure in pricing and investment behavior. Hong et al. (2019) show that the stock returns of food companies are determined by the severity of droughts in the countries where the firms are located. Bolton and Kacperczyk (2021) find that institutional holdings are negatively related to emission intensity. Bourdeau-Brien and Kryzanowski (2017) examine the impact of natural disasters by documenting that the shocks such as hurricanes, floods and episodes of extreme temperature affect US stock returns and volatilities. In our case, we select two proxies to monitor the intensity of climate change at the state-level, namely climate anomalies calculated as the difference between annual average temperature and long-term mean ($Abnormal\ Temperature$) obtained from NOAA and the number of extreme weather events (drought, wildfire, storm, hurricane, flooding) causing more than $1 billion economic losses ($Extreme\ Weather$) sourced from Universal Ecological Fund. Columns (5) and (6) decompose the sample into two groups based on the median value of $Abnormal\ Temperature$, whereas columns (7) and (8) perform a similar task based on the median value of $Extreme\ Weather$. Our findings collectively show that the effect of climate change exposure on equity premium is only significant for a sub-sample of firms already facing severe climate change due to their locations.

The third and last dimension is related to firms' financial constraints and probability of bankruptcy. Environmental performance of firms through sustainable growth targets, carbon-emission reductions and renewable energy implementation can improve external financing opportunities by alleviating financial constraints (Zhang and Lucey, 2022). Furthermore, prior works find that firms' distance-to-default is negatively correlated with carbon footprint (Capasso et al., 2020). We hypothesize that the effect of climate change exposure is amplified for firms with heightened financial constraints and the likelihood of default. To investigate this hypothesis, we use Compustat data by creating two indicators of firms' debt-repayment ability which are the ratio of total debt to capital ($Debt/Invested\ Capital$) and the multiple of EBITDA to interest expenses ($Interest\ Coverage$). In columns (9) and (10), we show that investors demand a larger premium when firm indebtedness is higher than the sample median threshold. In columns (11) and (12), we reach the conclusion that investors require a larger premium when firms' interest coverage is below the sample median value.

5. Conclusion

Using a comprehensive dataset, this study shows that an increase in climate change exposure directly elevates a firm's cost of equity, indicative of the market's interpretation of climate change as a risk to investment. Moreover, our paper elaborates on how the public's level of climate change awareness, the intensity of climate-related events, and the financial robustness of firms significantly modify the identified relationship.

Our findings carry several implications for policymakers, market participants, and firms. Policymakers should consider the potential impact of climate change on the cost of capital when formulating regulatory frameworks. Climate change-related policies and regulations can have significant implications for firms' financial performance and consequently affect market dynamics. In this regard, policies that promote transparency around firms' climate change exposure could contribute to more accurate pricing of risks and help prevent potential market distortions. For market participants, our study underlines the importance of integrating climate change considerations into investment decisions, suggesting that climate change can indeed be a source of systematic risk that could affect portfolio performance. As such, investors might need to re-evaluate their portfolio strategies to consider the implications of climate change for firms' financing costs. As for firms, our results imply that there are financial benefits to adopting sustainable practices and mitigating their exposure to climate change. With an increasing cost of equity associated with climate change exposure, firms that can reduce their climate change risks could potentially lower their cost of financing and gain a competitive advantage.

While our study provides valuable insights into the relationship between climate change exposure and the cost of equity, we acknowledge that there is still much to be learned about the implications of climate change for financial markets. A possible avenue for future research could involve further investigating the mechanisms through which climate change risks are priced into the cost of equity. This would involve exploring the role of information dissemination, investor beliefs, and market dynamics in the pricing of climate risks. Another potentially fruitful line of inquiry could involve examining how climate change exposure affects other dimensions of firm performance, such as profitability, innovation, and long-term growth.

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Table 1: Variable Definitions

Variables	Definitions	Data Sources
Panel A: Main Dependent and Control Variables		
CoE	The estimated cost of equity capital based on Capital Asset Pricing Model (CAPM)	Authors' Calculations, CRSP, Aswath Damodaran's webpage
CC_Exposure	The natural logarithm of one plus the firm-level climate change exposure indicator	Sautner et al. (2023)
Book-to-Market	Book value of equity as a fraction of market value of the equity	Compustat
Firm Size	The natural logarithm of total assets	Compustat
NPM	Net income as a fraction of total sales	Compustat
ROA	Operating income before depreciation as a fraction of total assets	Compustat
Leverage	Total liabilities as a fraction of total assets	Compustat
R&D	Research and development expenses as a fraction of total sales	Compustat
Panel B: Other Variables		
CC_Exposure_Opp	The natural logarithm of one plus the firm-level climate change exposure indicator related to opportunity shocks	Sautner et al. (2023)
CC_Exposure_Rg	The natural logarithm of one plus the firm-level climate change exposure indicator related to regulatory shocks	Sautner et al. (2023)
CC_Exposure_Ph	The natural logarithm of one plus the firm-level climate change exposure indicator related to physical shocks	Sautner et al. (2023)
CC_Exposure_Sector	Climate change exposure indicator averaged at 2-digit SIC sector classification	Authors' Calculations, Sautner et al. (2023)
Paris Withdrawal	A dummy variable taking the value of one after 2017 when US withdrew from Paris Agreement, otherwise zero	Authors' Calculations
High Exposure	A dummy variable taking the value of one if the firm-level climate change exposure indicator exceeds sample median threshold in 2017, otherwise zero	Authors' Calculations, Sautner et al. (2023)
Beta	Estimated stock return beta	Authors' Calculations, CRSP
P/E	Price-to-earnings ratio	Compustat
EVM	Multiple of enterprise value to EBITDA	Compustat
Cash	Cash balance as a fraction of total liabilities	Compustat

CAPEX	Capital expenditures as a fraction of total assets	Compustat
CoD	Interest expenses as a fraction of total debt	Compustat
E-Score	Environmental pillar of firm-level Refinitiv ESG score	Thomson Reuters
Democrat	State-level political orientation measured as the proportion of votes gained by Democrat Party candidates from constituency returns for elections to the US Senate	MIT Election Data and Science Lab
Climate Attention Index	State-level indicator of media coverage on climate change measured as the annual sum of daily news counts regarding climate change theme	Bloomberg Terminal
Abnormal Temperature	State-level climate anomalies measured as the difference between annual average temperature and long-term mean (1901-2022)	NOAA
Extreme Weather	State-level number of extreme weather events (drought, wildfire, severe storm, hurricane, flooding) causing more than $1 billion economic losses	Universal Ecological Fund
Debt/Invested Capital	Total debt (long-term and current) as a fraction of total invested capital	Compustat
Interest Coverage	Multiple of earnings before interest and taxes to interest and related expenses	Compustat

Notes: This table reports variable definitions and data sources of the main and supplementary variables used in this study. Our sample includes 1,238 firms over the period 2010-2021.

Table 2: Summary Statistics

Variables	Obs.	Mean	Std. Dev.	Median	P5	P95
CoE	8,749	0.0672	0.0268	0.0655	0.0245	0.1140
CC_Exposure	8,749	0.0008	0.0018	0.0003	0.0000	0.0037
Book-to-Market	8,356	0.5959	0.5394	0.4528	0.0723	1.5855
Firm Size	8,749	6.7659	1.8754	6.6712	3.6839	9.9680
NPM	8,665	-0.3504	2.0122	0.0314	-1.3548	0.2644
ROA	8,723	0.0545	0.1972	0.0906	-0.3664	0.2907
Leverage	8,677	0.2494	0.2456	0.1887	0.0000	0.7198
R&D	8,732	0.2272	0.9750	0.0000	0.0000	0.6973

Notes: This table reports summary statistics of the sample. Our sample includes 1,238 firms over the period 2010-2021.

Table 3: Baseline Results

	(1) CoE	(2) CoE	(3) CoE	(4) CoE
CC_Exposure	0.8028***	0.8375***	11.8969***	11.9794***
	(0.2921)	(0.2974)	(4.3846)	(4.5721)
Book-to-Market		-0.0029**		-0.0394*
		(0.0013)		(0.0206)
Firm Size		0.0044***		0.0649***
		(0.0013)		(0.0177)
NPM		-0.0009**		-0.0099**
		(0.0004)		(0.0044)
ROA		-0.0097*		-0.1273*
		(0.0054)		(0.0717)
Leverage		0.0101*		0.1355*
		(0.0056)		(0.0766)
R&D		-0.0013*		-0.0128
		(0.0007)		(0.0086)
Obs.	7,248	6,839	7,248	6,839
Method	OLS	OLS	Poisson	Poisson
Firm Controls	No	Yes	No	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.486	0.503		
Pseudo R^2			0.014	0.014

Notes: This table presents the estimation results of the baseline model specified in Equation (2). The sample includes the observations of 1,238 firms over the period 2010-2021. In all columns, the dependent variable is the cost of equity (CoE) calculated in line with Equation (1). Columns (1) and (3) are the parsimonious specifications, while columns (2) and (4) involve firm-level controls ($Book-to-Market$, $Firm\,Size$, NPM, ROA, $Leverage$ and $R\&D$). Columns (1) and (2) are estimated with OLS, while columns (3) and (4) are estimated with Poisson regression. The main independent variable is $CC\_Exposure$ index developed by Sautner et al. (2023). In all columns, we control for firm and year fixed effects. Detailed variable definitions are available in Table 1. Standard errors clustered at industry-level are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4: Sub-Components of Climate Change Exposure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CoE	CoE	CoE	CoE	CoE	CoE	CoE	CoE
CC_Exposure_Opp	1.6728***			1.7909***	24.8040***			26.3569***
	(0.5567)			(0.6009)	(7.7957)			(8.1108)
CC_Exposure_Rg		-1.0045		-2.4659		-16.3201		-35.9336
		(3.8108)		(4.2901)		(57.1842)		(63.4047)
CC_Exposure_Ph			-0.9705	-1.2282			-29.0562	-29.7921
			(7.4186)	(7.6998)			(102.7913)	(108.0228)
Obs.	6,839	6,839	6,839	6,839	6,839	6,839	6,839	6,839
Method	OLS	OLS	OLS	OLS	Poisson	Poisson	Poisson	Poisson
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.503	0.503	0.503	0.503				
Pseudo R^2					0.014	0.014	0.014	0.014

Notes: This table presents the estimation results of the baseline model specified in Equation (2) for sub-components of climate change exposure, separately. The sample includes the observations of 1,238 firms over the period 2010-2021. In all columns, the dependent variable is the cost of equity (CoE) calculated in line with Equation (1). Columns (1) to (3) (and (5) to (7)) involve the main independent variables $CC\_Exposure\_Opp$, $CC\_Exposure\_Rg$ and $CC\_Exposure\_Ph$ developed by Sautner et al. (2023) serving as proxy for opportunity, regulatory and physical climate risks, respectively. Columns (4) and (8) estimate saturated models incorporating all sub-components of climate change exposure simultaneously. All columns account for firm and year fixed effects as well as firm-level controls ($Book-to-Market$, $Firm\ Size$, NPM, ROA, $Leverage$ and $R\&D$). Columns (1), (2), (3) and (4) are estimated with OLS, while columns (5), (6), (7) and (8) are estimated with Poisson regression. Detailed variable definitions are available in Table 1. Standard errors clustered at industry-level are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

.

Table 5: Additional Analysis for Endogeneity Concerns

	(1) CoE	(2) CC_Exposure	(3) CoE	(4) CoE	(5) CoE
CC_Exposure	0.8444**			1.2659*	
	(0.3736)			(0.7209)	
CC_Exposure_Sector		0.7655***			
		(0.1056)			
CC_Exposure_Fitted			4.1934**		
			(2.0728)		
CoE(t-1)				0.5250***	
				(0.0671)	
CoE(t-2)				0.0617**	
				(0.0261)	
Paris Withdrawal x High Exposure					-0.0023*
					(0.0012)
Paris Withdrawal					-0.0041***
					(0.0012)
High Exposure					0.0043**
					(0.0016)
Obs.	6,823	6,839	6,839	5,840	3,248
Method	Entropy Balancing	IV (First Step)	IV (Second Step)	System GMM	DiD
Firm Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	No
Year FE	Yes	Yes	Yes	Yes	No
R^2	0.592				0.094
Centered R^2		0.253			
Kleibergen-Paap rk LM Statistic		5.41			
p-value		0.020			
Kleibergen-Paap Wald rk F Statistic		52.57			
Stock-Yogo Test Critical Value at 10%		16.38			
AR(1) Test p-value				0.000	

AR(2) Test p-value	0.002
AR(3) Test p-value	0.678
Hansen Test Chi-Squared Statistic	55.05
p-value	0.473

Notes: This table presents the estimation results of alternative methods and research designs to alleviate endogeneity concerns. In column (1), we repeat the baseline model by using the entropy-balanced sample. In columns (2) and (3), we run the first-step and second-step regressions of instrumental variable estimation which instruments $CC\_Exposure$ with the time-varying sector-average of the index itself, termed as $CC\_Exposure\_Sector$. In column (4), we follow the dynamic panel by using system GMM estimation technique. Column (5) presents the results concerning difference-in-differences analysis with the main variable of interest taken as $Paris\ Withdrawal\ x\ High\ Exposure$ interaction term. All columns involve firm-level controls ($Book-to-Market$, $Firm\ Size$, NPM, ROA, $Leverage$ and $R\&D$). Columns (1) to (4) incorporate firm and year fixed effects. Detailed variable definitions are available in Table 1. Standard errors clustered at industry-level are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6: Robustness Checks

	(1) Coefficient (CC_Exposure)	(2) S. E.	(3) Obs.
(1) Two-way S. E. clustering	0.8375**	(0.4058)	6,839
(2) S. E. clustered at firm level	0.8375*	(0.4594)	6,839
(3) Dependent variable: Beta	17.9270***	(6.1467)	6,839
(4) Excluding Covid Period	0.7883*	(0.4671)	5,807
(5) Additional control variables	0.7443**	(0.2938)	6,791
(6) Industry-by-year fixed effects	0.6926**	(0.3354)	6,737
(7) Excluding financial firms	0.8300***	(0.2975)	6,786
(8) Contemporaneous value of CC_Exposure	0.4928**	(0.2378)	6,839
(9) Excluding zero observations for CC_Exposure	0.8583***	(0.3053)	5,618
(10) Placebo estimation: CoD	3.5626	(3.1652)	5,256
(11) Firms with at least 5-years of observations	0.8909***	(0.3230)	6,455
(12) Controlling for firm-level E-Score	0.8346***	(0.2974)	6,839

Notes: This table presents the estimation results of robustness checks for the specification presented in column (2) of Table 3. Columns (1), (2) and (3) report the coefficient attached to main independent variable $CC\_Exposure$, standard error and number of observations, respectively. In rows (1) and (2) we cluster standard errors at industry-year and firm levels. In row (3), we replace the outcome variable CoE with the firm-level measure of systematic risk ($Beta$). In row (4), we restrict the sample period coverage to the pre-2020 period. In row (5), we expand the set of firm-level controls by adding the series P/E, EVM, $Cash$ and $CAPEX$. In row (6), we replace year fixed effects with higher degree industry-by-year fixed effects. Row (7) drops a few observations belonging to financial firms. In row (8) we examine the effect of contemporaneous value of $CC\_Exposure$ instead of lagged values, whereas, in row (9), we omit the zero observations corresponding to $CC\_Exposure$. In row (10), we replace the outcome variable related to the cost of equity financing with an indicator summarizing the cost of debt financing (CoD). In row (11), we restrict the sample to firms with at least 5-years of observations to alleviate survivorship bias. In row (12), we control for firm-level environmental score ($E - Score$). Unless stated otherwise, all rows account for firm and year fixed effects as well as firm-level controls (Book-to-Market, Firm Size, NPM, ROA, Leverage and R&D). Detailed variable definitions are available in Table 1. Unless otherwise stated, standard errors clustered at industry-level are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

Table 7: Underlying Mechanisms

Panel A	(1) CoE (Democrat>Median)	(2) CoE (Democrat<Median)	(3) CoE (Climate Attention Index>Median)	(4) CoE (Climate Attention Index<Median)
CC_Exposure	1.5348**	0.1026	1.4685**	0.4459
	(0.6284)	(0.6009)	(0.6162)	(0.7492)
Obs.	3,628	3,027	3,561	2,955
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.460	0.559	0.485	0.548
Panel B	**(5) CoE (Abnormal Temperature>Median)**	**(6) CoE (Abnormal Temperature <Median)**	**(7) CoE (Extreme Weather>Median)**	**(8) CoE (Extreme Weather<Median)**
CC_Exposure	0.8469*	0.8876	1.1193**	0.2992
	(0.4421)	(0.5827)	(0.4537)	(0.4368)
Obs.	3,554	3,048	3,454	3,385
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.524	0.502	0.552	0.463
Panel C	**(9) CoE (Debt/Invested Capital>Median)**	**(10) CoE (Debt/Invested Capital<Median)**	**(11) CoE (Interest Coverage>Median)**	**(12) CoE (Interest Coverage<Median)**
CC_Exposure	0.9977*	0.5804	0.6111	1.1606*
	(0.5408)	(0.4984)	(0.4990)	(0.6658)
Obs.	3,343	3,322	2,813	2,460
Firm Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adj. R^2	0.559	0.492	0.590	0.487

Notes: This table presents the estimation results of the underlying mechanisms. We repeat the baseline model specified in Equation (2) for different sub-samples. Panel A focuses on the level of attention given to climate risks. Columns (1) and (2) disentangle the firms located in states with the proportion of Democrat Party-inclined voting percentage ($Democrat$) being higher and lower than sample median value, respectively. Columns (3) and (4) separate the firms located in states with the frequency of media coverage of climate topics ($Climate\ Attention\ Index$) being higher and lower than sample median value, respectively. Panel B focuses on the severity of climate change realizations. Columns (5) and (6) disentangle the firms located in states with the average abnormal temperature ($Abnormal\ Temperature$) being higher and lower than sample median value, respectively. Columns (7) and (8) separate the firms located in states with the number of extreme weather events ($Extreme\ Weather$) being higher and lower than sample median value, respectively. Panel C focuses on the extent of financial constraints and the likelihood of firm bankruptcy. Columns (9) and (10) disentangle the firms with the ratio of debt to invested capital ($Debt/Invested\ Capital$) being higher and lower than sample median value, respectively. Columns (11) and (12) separate the firms with the ratio of earnings before interest and taxes to interest and related expenses ($Interest\ Coverage$) being higher and lower than sample median value, respectively. All columns account for firm and year fixed effects as well as firm-level controls ($Book-to-Market$, $Firm\ Size$, NPM, ROA, $Leverage$ and $R\&D$). Detailed variable definitions are available in Table 1. Standard errors clustered at industry-level are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

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