



Climate change exposure and the use of short-term debt

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ABSTRACT

This study investigates the relationship between a firm's exposure to climate change and its preference for short-term debt. Using a comprehensive dataset of U.S. firms from 2002 to 2020 and employing a novel measure of firm-specific climate change exposure, the findings indicate that firms with high exposure are more likely to use short-term debt, particularly for opportunity-related climate change exposure. Propensity score matching and additional robustness analyses support the robustness of our findings. In addition, cross-sectional subsample analyses further suggest that the effect is magnified in climate-sensitive groups and financially constrained firms.

1. Introduction

Climate change poses a major challenge to the global economy and is expected to significantly impact businesses (Burke et al., 2015; Dietz et al., 2016). Consequently, strategic adaptation is essential in corporate financial decision-making. Although research has begun to shed light on the impact of climate risk on financial behavior, such as Ginglinger and Moreau's (2023) finding regarding reduced leverage and Javadi et al.'s (2023) observation of increased cash holdings in exposed firms,¹ the question of debt maturity choice remains largely unexplored. This study aims to address this crucial gap by investigating the potential link between climate change exposure and short-term debt preference.

The choice between short- and long-term debts is critical for firms as it significantly impacts their financial stability and profitability. Prior studies focus on the determinants of corporate debt maturity structure, building on the work of Stohs and Mauer (1996) (Custódio et al., 2013; Ee et al., 2023; Huang et al., 2016). Recent studies incorporate the impact of market uncertainty on debt maturity preferences. Hasan et al. (2022) suggest that firms facing volatile oil prices favor the low upfront costs and flexibility of short-term debt, despite increased refinancing risk and cost. Similarly, Datta et al. (2019) and Tran and Phan (2022) find that high policy uncertainty leads firms to gravitate toward the relatively quick renegotiation potential of short-term debt.

Building on these insights, this study hypothesizes that firms facing high climate change risk exhibit a preference for short-term debt. From an uncertainty management perspective, short-term debt is preferred for managing the uncertainty associated with climate change. Climate change can significantly impact businesses, leading to increased costs, operational disruptions, and regulatory changes (Burke et al., 2015; Dietz et al., 2016). These factors can increase firms' cash flow volatility and heighten their default risk in adverse scenarios. Faced with borrowers' higher default risks induced by high climate change exposure, creditors may choose to protect their interests by imposing more stringent debt terms. These terms may include shorter debt maturities, higher interest rates,

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¹ As additional examples of previous literature, Ding et al. (2021) find that climate change risk can lead to earnings management, and Hossain and Masum (2022) report that climate change risk can affect CEO equity incentives.

and more restrictive debt covenants. Short-term debt offers several advantages that make it particularly suitable for managing climate change uncertainty. First, it provides firms with greater flexibility in adapting to changing climate conditions. Compared with long-term debt, shorter debt maturities allow firms to adjust their debt levels more easily, which can help manage unexpected costs or disruptions caused by climate change. Prior studies have also revealed a positive relationship between uncertainty and the use of short-term debt (Datta et al., 2019; Hasan et al., 2022; Tran and Phan, 2022). Second, short-term debt can provide firms with a buffer against investment opportunities that may be volatile owing to climate change exposure. While climate change is expected to create various investment opportunities, the market is still developing clear definitions and standards for green investment (Dumitrescu et al., 2022; Economist, 2021). In this context, short-term debt allows firms to preserve debt capacity for investment in future growth opportunities (Graham and Harvey, 2001).

To empirically test our hypothesis, this study leverages a comprehensive dataset of U.S. firms spanning 2002 to 2020. The current analysis centers on Sautner et al.'s (2023a) pioneering firm-level climate change exposure measure, derived through machine learning analysis of earnings call transcripts. This innovative approach allows us to capture the nuanced and multifaceted nature of climate risk faced by individual firms. Our analysis reveals that firms with higher climate change exposure are more likely to utilize short-term debt, even when controlling for a range of factors influencing debt choices. Notably, opportunity-related climate change exposure emerges as a particularly potent driver of short-term debt usage. And, several robustness tests, including propensity score matching (PSM), an alternative measure, firm fixed effects, and Tobit analyses, further strengthen the robustness of our results. In addition, cross-sectional subsample analyses reveal that the magnitude of this relationship intensifies within climate-sensitive and financially constrained firms.

This study makes several significant contributions to the literature on the relationship between climate change and corporate finance. First, it explores the impact of climate change exposure on debt maturity choices, expanding the literature on the economic implications of climate change beyond established areas such as leverage and cash holdings. Second, this study delves beyond simplistic proxies and captures the diverse nuances of climate change exposures faced by individual firms, enriching the discourse on the determinants of debt maturity by incorporating a comprehensive understanding of climate change. Third, this study identifies opportunity-related exposure as a key driver of short-term debt preference, offering vital insights for both firms and policymakers to navigate the complexities of green ventures and their associated financial management.

The remainder of this paper is organized as follows. Section 2 presents the research design, Section 3 reports the empirical results, and Section 4 concludes the paper.

2. Research design

2.1. Data

Our primary sample comprises all publicly listed U.S. firms in the Compustat database from 2002 to 2020. Firm-level financial and debt maturity information are obtained from Compustat and stock price data from the Center for Research in Security Prices. Additionally, firm-level climate change exposure data are obtained from the study by Sautner et al. (2023a). These three datasets are merged and exclude firms from the financial (SIC 4900–4999) and utility (SIC 6000–6999) industries. Furthermore, all continuous variables are winsorized at their 1st and 99th percentiles. Our final sample comprises 40,291 firm-year observations.

2.2. Measurement

2.2.1. Short-term debt

Prior studies on debt maturity typically use the proportion of debt maturing within a specified timeframe to represent the debt maturity structure. For instance, Hasan et al. (2022) and Huang and Shang (2019) employ the proportion of debt due within three years (*STDebt3*) and five years (*STDebt5*) as proxies for debt maturity. However, Freund et al. (2023) use the proportion within one year (*STDebt1*) and four years (*STDebt4*). Following Shang (2021), we employ the ratio of debt maturing within one year to total debt (*STDebt1*) as the primary measure of short-term debt usage. For robustness checks, we also utilize four alternative measures of debt maturity: *STDebt2* to *STDebt5*, representing the proportion of short-term debt maturing within two to five years, respectively.²

2.2.2. Climate change exposure

We utilize the Climate Change Exposure (*CCEXP*) metric developed by Sautner et al. (2023a).³ This variable captures all three basic dimensions of climate change: opportunity, regulatory, and physical climate change bigrams. The *CCEXP* variable ranges from zero to one, with a higher value indicating a greater level of climate change exposure for the firm. Details of these variables are defined in Appendix A.

² Consistent with prior studies (e.g., Brockman et al., 2010), we replace short-term debt ratios exceeding one with one and all negative short-term debt ratios with zero.

³ This measure quantifies the relative frequency of pre-defined climate change bigrams within the transcript, normalized by the total number of bigrams present. Furthermore, we employ annual-unit variables. Sautner et al. (2023a) create an annual measure for each firm by averaging the quarterly measures. <https://osf.io/preprints/socarxiv/yq27d/>

Table 1
Summary statistics and correlation matrix.

Panel A. Summary statistics								
	N	Mean	STD	p5	p25	Median	p75	p95
$STDebt1_{t+1}$	40,291	0.341	0.397	0	0.02	0.125	0.722	1
$STDebt2_{t+1}$	40,291	0.433	0.401	0	0.064	0.268	0.996	1
$STDebt3_{t+1}$	40,291	0.531	0.393	0	0.153	0.458	1	1
$STDebt4_{t+1}$	40,291	0.63	0.369	0.013	0.288	0.694	1	1
$STDebt5_{t+1}$	40,291	0.729	0.325	0.073	0.468	0.929	1	1
$Size_t$	40,291	6.875	1.996	3.683	5.487	6.806	8.195	10.301
$Leverage_t$	40,291	0.24	0.257	0	0.022	0.2	0.364	0.654
MTB_t	40,291	2.123	1.788	0.853	1.19	1.6	2.399	5.099
$AbEarn_t$	40,291	-0.021	0.392	-0.322	-0.026	0.004	0.027	0.238
ATM_t	40,291	9.255	12.275	0.659	2.315	5.092	11.73	29.222
ATV_t	40,291	0.02	0.013	0.006	0.011	0.017	0.026	0.044
$R\&D_t$	40,291	0.059	0.174	0	0	0.005	0.066	0.263
$R\&D\ dummy_t$	40,291	0.548	0.498	0	0	1	1	1
$AltmanZ_t$	40,291	3.809	6.601	-2.304	1.412	2.951	5.053	13.928
$TermPRM_t$	40,291	1.658	1.133	-0.3	0.72	1.73	2.55	3.41
$CCEXP_t$	40,291	0.753	1.886	0	0.088	0.264	0.65	2.968
$CCEXP_t^{OP}$	40,291	0.288	0.992	0	0	0.065	0.217	1.126
$CCEXP_t^{RG}$	40,291	0.041	0.258	0	0	0	0	0.185
$CCEXP_t^{PH}$	40,291	0.012	0.098	0	0	0	0	0.076

Panel B. Correlation matrix					
	$STDebt1_{t+1}$	$STDebt2_{t+1}$	$STDebt3_{t+1}$	$STDebt4_{t+1}$	$STDebt5_{t+1}$
$CCEXP_t$	0.016**	0.021***	0.020***	0.017***	0.017***
$CCEXP_t^{OP}$	0.034***	0.038***	0.034***	0.029***	0.028***
$CCEXP_t^{RG}$	0.003	0.006	0.007	0.004	0.003
$CCEXP_t^{PH}$	-0.026***	-0.024***	-0.021***	-0.020***	-0.017***

Notes: This table presents the descriptive statistics of the variables used in the study and the Pearson correlations for the variables of interest. All climate change exposure measures are multiplied by 1000 for exposition (Feng et al., 2022). All detailed descriptions and data sources for these variables are provided in Appendix A. The sample spans the period 2002–2020. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

2.3. Empirical models

This study employs the following ordinary least squares regression model to estimate the association between climate change risk exposure and debt maturity structure:

$$STDebt_{it,t+1} = \alpha + \beta CCEXP_{it} + \gamma CONTROLS_{it} + FIXED\ EFFECTS + \varepsilon_{it,t+1}, \quad (1)$$

where $STDebt_{it,t+1}$ is the dependent variable representing short-term debt in year $t + 1$, and $CCEXP_{it}$ is the measure of firm-specific exposure to climate change in year t and is the main explanatory variable in this study. Additionally, following prior literature (Datta et al., 2021; Hasan et al., 2022; Huang and Shang, 2019; Shang, 2021), we control for firm size (*Size*), financial leverage (*Leverage*), market-to-book ratio (*MTB*), abnormal earnings (*AbEarn*), asset maturity (*ATM*), asset volatility (*ATV*), research and development expenses (*R&D*), research and development expenses dummy variable (*R&D dummy*), Altman (1968) Z-score (*AltmanZ*), and the term premium of interest rate (*TermPRM*). Furthermore, Eq. (1) includes industry- and year-fixed effects, and the standard errors are clustered at the firm level.

3. Empirical results

3.1. Descriptive statistics

Panel A of Table 1 presents the descriptive statistics of the main variables used in this study. The mean of $STDebt1$ is 0.341, indicating that short-term debt accounts for 34.1 % of the total debt. The values of the alternative short-term debt ratio variables range from 0.433 for $STDebt2$ and increase monotonically to 0.729 for $STDebt5$. These values are similar to those reported in previous studies (Datta et al., 2019; Hasan et al., 2022; Huang and Shang, 2019). The main explanatory variable of this study, $CCEXP$, has a mean of 0.753 and a standard deviation of 1.886. $CCEXP$ and its three alternative variables closely align with values found in the literature (Sautner et al., 2023a).

Panel B of Table 1 reports the Pearson correlations between debt maturity and climate change exposure. The findings indicate significant positive correlations between the climate change exposure variable and all debt maturity variables. These findings support our hypothesis that firms with high climate change exposure are significantly likely to have relatively short debt maturities.

Table 2

Baseline regression: Climate change exposure and short-term debt.

	(1) <i>STDebt1_{t+1}</i>	(2) <i>STDebt2_{t+1}</i>	(3) <i>STDebt3_{t+1}</i>	(4) <i>STDebt4_{t+1}</i>	(5) <i>STDebt5_{t+1}</i>
<i>CCEXP_t</i>	0.006** (2.283)	0.006*** (2.842)	0.005*** (2.700)	0.004** (2.489)	0.003** (2.269)
<i>Size_t</i>	−0.059*** (−26.637)	−0.064*** (−29.267)	−0.066*** (−31.455)	−0.063*** (−32.925)	−0.057*** (−32.054)
<i>Leverage_t</i>	−0.383*** (−10.980)	−0.371*** (−11.206)	−0.309*** (−11.235)	−0.202*** (−10.184)	−0.128*** (−8.469)
<i>MTB_t</i>	−0.003 (−1.494)	−0.004* (−1.723)	−0.004** (−2.022)	−0.005** (−2.569)	−0.003** (−1.995)
<i>AbEarn_t</i>	−0.027*** (−5.069)	−0.028*** (−5.468)	−0.027*** (−5.822)	−0.028*** (−6.893)	−0.024*** (−7.242)
<i>ATM_t</i>	0.024 (0.892)	0.018 (0.692)	0.013 (0.501)	0.004 (0.144)	−0.033 (−1.309)
<i>ATV_t</i>	1.838*** (6.067)	1.680*** (6.143)	1.216*** (5.177)	0.746*** (3.700)	0.159 (0.896)
<i>R&D_t</i>	0.144*** (3.142)	0.123*** (2.935)	0.085*** (2.715)	0.041** (2.333)	0.002 (0.166)
<i>R&D dummy_t</i>	0.047*** (4.557)	0.048*** (4.722)	0.041*** (4.280)	0.030*** (3.428)	0.012 (1.392)
<i>AltmanZ_t</i>	0.007*** (10.758)	0.005*** (8.230)	0.003*** (6.457)	0.002*** (5.710)	0.002*** (5.127)
<i>TermPRM_t</i>	0.007 (1.029)	0.006 (0.884)	0.010 (1.433)	0.013** (2.042)	0.014** (2.381)
<i>Constant</i>	0.731*** (30.401)	0.870*** (37.288)	0.982*** (44.246)	1.054*** (53.621)	1.121*** (63.138)
<i>Observations</i>	40,291	40,291	40,291	40,291	40,291
<i>Adjusted R²</i>	0.386	0.380	0.345	0.299	0.281
<i>Ind FE</i>	Yes	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the regression model results for the effects of climate change exposure on short-term debt usage. Detailed descriptions and data sources for these variables are provided in [Appendix A](#). All results are provided after controlling for industry- and fiscal-year fixed effects. The t-values based on standard errors clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

3.2. Baseline results

We conduct a baseline regression to examine the association between firms' climate change exposures and their short-term debt usage. The results are reported in [Table 2](#). We empirically analyze this relationship using five different short-term debt variables based on prior literature ([Freund et al., 2023](#); [Hasan et al., 2022](#); [Huang and Shang, 2019](#); [Shang, 2021](#)). The correlation coefficient of *STDebt1* in Column 1 is significant at 0.006. *STDebt2*, *STDebt3*, *STDebt4*, and *STDebt5* in Columns 2–5 also show significant positive correlation coefficients. These results support the hypothesis that firms with high climate change exposure tend to use more short-term debt. However, the correlation coefficient decreases when the definition of short-term debt is extended from less than one year to five years. These results suggest that a firm's climate change exposure is strongly linked to its use of short-term debt with shorter maturities.

In addition to the baseline analysis, we conduct an analysis to investigate the relationship between climate change exposure and short-term debt usage, using three categories of bigram topics related to climate-related opportunities, regulatory shocks, and physical shocks to create three more granular climate change exposure variables ([Sautner et al., 2023a](#)). We rerun the baseline regression using these alternative variables. The results are reported in [Table 3](#). The empirical analysis reveals that opportunity-related climate change exposure has a significant positive impact on the use of short-term debt. The results suggest that firms exposed to potential investment opportunities arising from climate change tend to rely heavily on short-term debt. This can be interpreted based on the literature that by leveraging short-term debt, firms facing such opportunities can maintain the flexibility to access additional capital when needed without being tied down to long-term debt structures before the market matures ([Graham and Harvey, 2001](#)). These results are also consistent with those reported by [Sautner et al. \(2023b\)](#).⁴

⁴ [Sautner et al. \(2023b\)](#) find that the risk premium for climate change exposure is primarily driven by climate-related opportunity shocks. This suggests that climate change can present both risks and opportunities for firms.

Table 3
Short-term debt and three types of climate change exposures.

	(1) $STDebt1_{t+1}$	(2) $STDebt1_{t+1}$	(3) $STDebt1_{t+1}$	(4) $STDebt1_{t+1}$
$CCEXP^{OP}_t$	0.013*** (3.370)			0.012*** (3.183)
$CCEXP^{RG}_t$		0.028** (2.050)		0.021 (1.490)
$CCEXP^{PH}_t$			−0.041* (−1.671)	−0.051** (−1.969)
$Size_t$	−0.059*** (−26.661)	−0.059*** (−26.734)	−0.059*** (−26.763)	−0.059*** (−26.707)
$Leverage_t$	−0.384*** (−10.997)	−0.383*** (−10.968)	−0.383*** (−10.970)	−0.384*** (−10.990)
MTB_t	−0.003 (−1.501)	−0.003 (−1.439)	−0.003 (−1.370)	−0.003 (−1.465)
$AbEarn_t$	−0.027*** (−5.062)	−0.027*** (−5.072)	−0.027*** (−5.070)	−0.027*** (−5.037)
ATM_t	0.024 (0.900)	0.024 (0.895)	0.024 (0.900)	0.024 (0.919)
ATV_t	1.828*** (6.038)	1.868*** (6.150)	1.896*** (6.243)	1.811*** (5.984)
$R\&D_t$	0.145*** (3.136)	0.143*** (3.137)	0.142*** (3.129)	0.144*** (3.134)
$R\&D\ dummy_t$	0.047*** (4.548)	0.048*** (4.620)	0.048*** (4.636)	0.047*** (4.559)
$AltmanZ_t$	0.007*** (10.774)	0.007*** (10.680)	0.007*** (10.652)	0.007*** (10.765)
$TermPRM_t$	0.007 (0.987)	0.007 (1.115)	0.008 (1.155)	0.007 (1.031)
$Constant$	0.733*** (30.535)	0.733*** (30.552)	0.735*** (30.602)	0.732*** (30.534)
$Observations$	40,291	40,291	40,291	40,291
$Adjusted R^2$	0.386	0.386	0.386	0.387
$Ind\ FE$	Yes	Yes	Yes	Yes
$Year\ FE$	Yes	Yes	Yes	Yes

Notes: This table presents the results of the regression, analyzing the effect of climate change exposure on short-term debt usage, using three alternative variables of the $CCEXP$ to capture more granular aspects of climate change exposure. $CCEXP^{OP}$ measures a firm's opportunity for climate change exposure by assessing the frequency of words related to climate change opportunities. $CCEXP^{RG}$ captures a firm's regulatory climate change exposure by measuring the frequency of words related to climate change regulations. $CCEXP^{PH}$ measures a firm's exposure to physical climate change by examining the frequency of words related to natural disasters and climate change. Detailed descriptions and data sources for these variables are provided in [Appendix A](#). All results are provided after controlling for industry- and fiscal-year fixed effects. The t-values based on standard errors clustered by the firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

3.3. Propensity score matching analysis

This study employs PSM to mitigate potential endogeneity concerns ([Rosenbaum and Rubin, 1983](#)). We generate one-to-one and one-to-three matched samples for firms with low climate change exposure to ensure they share key characteristics with those in the high-exposure group.⁵ Replicating the regression analysis on these matched samples yields robust results.

As presented in Columns 1 and 2, the coefficients of $CCEXP$ and $CCEXP^{OP}$ in the one-to-one matched sample are significant at the 1 % level of 0.006 and 0.100, respectively. Similarly, Columns 3 and 4 show significant coefficient values of both measures in the one-to-three matched samples. These robust results offer compelling support for our initial hypothesis.

3.4. Additional robustness tests

We conduct additional robustness tests to strengthen our empirical findings, as shown in [Appendix B](#). First, following previous literature such as [Dang and Phan \(2016\)](#) and [Shang \(2021\)](#), we revisit our baseline analysis using an alternative measure of short-term debt ($STNP$). The results reveal a statistically significant positive correlation similar to our previous findings. Second, to address concerns related to unobserved heterogeneity and time-invariant firm characteristics, we rerun the baseline analysis with firm fixed effects. While the statistical significance diminishes for opportunity-related climate exposure, the firm-specific climate change

⁵ In Columns 1 and 3 of [Table 4](#), we divide the climate change exposure variable into high- and low-exposure groups based on the median value. Propensity scores are then estimated using a logit regression model, considering all control variables and industry. We employ nearest neighbor 1:1 and 1:3 matchings based on the propensity score to create new matched samples. In Columns 2 and 4, we perform sample matching using the median value of the climate-related opportunity variable in the same manner.

Table 4
Propensity score matching.

	(1) $STDebt1_{t+1}$ 1:1 matched	(2) $STDebt1_{t+1}$	(3) $STDebt1_{t+1}$ 1:3 matched	(4) $STDebt1_{t+1}$
<i>CCEXP</i>	0.006** (2.361)		0.006** (2.478)	
<i>CCEXP</i> ^{OP}		0.100** (2.090)		0.105** (2.214)
<i>Size</i> _{<i>t</i>}	−0.056*** (−23.672)	−0.057*** (−23.356)	−0.057*** (−25.220)	−0.057*** (−24.808)
<i>Leverage</i> _{<i>t</i>}	−0.356*** (−9.674)	−0.369*** (−10.613)	−0.371*** (−10.859)	−0.391*** (−11.728)
<i>MTB</i> _{<i>t</i>}	−0.006** (−2.458)	−0.002 (−0.642)	−0.004* (−1.817)	−0.003 (−1.063)
<i>AbEarn</i> _{<i>t</i>}	−0.022*** (−2.912)	−0.023*** (−3.423)	−0.026*** (−4.129)	−0.028*** (−4.862)
<i>ATM</i> _{<i>t</i>}	0.028 (0.961)	0.013 (0.420)	0.005 (0.205)	0.023 (0.870)
<i>ATV</i> _{<i>t</i>}	2.013*** (5.598)	1.802*** (4.938)	1.914*** (5.789)	1.805*** (5.543)
<i>R&D</i> _{<i>t</i>}	0.262*** (6.414)	0.153*** (2.597)	0.164*** (3.506)	0.143*** (2.886)
<i>R&D dummy</i> _{<i>t</i>}	0.046*** (4.348)	0.051*** (4.670)	0.051*** (4.890)	0.052*** (5.065)
<i>AltmanZ</i> _{<i>t</i>}	0.008*** (11.275)	0.006*** (8.055)	0.007*** (10.842)	0.007*** (9.444)
<i>TermPRM</i> _{<i>t</i>}	0.000 (0.050)	0.014 (1.566)	0.003 (0.335)	0.006 (0.797)
<i>Constant</i>	0.696*** (24.700)	0.696*** (24.985)	0.706*** (27.657)	0.711*** (27.972)
<i>Observations</i>	30,686	30,962	37,710	37,992
<i>Adjusted R</i> ²	0.379	0.373	0.378	0.377
<i>Ind FE</i>	Yes	Yes	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes

Notes: This table presents the results of the propensity score matching analysis. Detailed descriptions and data sources for these variables are provided in [Appendix A](#). All results are provided after controlling for industry- and fiscal-year fixed effects. The t-values based on standard errors clustered by firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

exposure variables exhibit a statistically significant positive correlation in robustness tests with firm fixed effects. Finally, as our dependent variable (short-term debt) ranges from 0 to 1, we employ the Tobit regression model to account for its limited range, as suggested by [Asongu et al. \(2021\)](#). The results demonstrate a statistically significant positive correlation, consistent with our previous findings. Overall, the robustness tests in [Appendix B](#) further support our empirical results.

3.5. Cross-sectional subsample analysis

The findings indicate that climate change exposure is positively associated with short-term debt usage. We hypothesize that this relationship is more pronounced for firms sensitive to climate change. To test this hypothesis, we conduct a cross-sectional subsample analysis using two approaches: climate-sensitive industries and labor intensity. Panel A of [Table 5](#) presents the results of the cross-sectional subsample analysis by climate-sensitive industries. The findings suggest that the relationship between climate change exposure and short-term debt usage is significant for firms in climate-sensitive industries. Panel B of [Table 5](#) presents the results of the cross-sectional subsample analysis by labor intensity. We posit that the relationship between climate change exposure and short-term debt usage is particularly pronounced for labor-intensive firms. This hypothesis stems from the unique vulnerabilities that labor-intensive firms face in the wake of climate change-related disruptions. Climate change can directly impact worker productivity, especially in labor-intensive industries. Extreme weather events, such as heat waves, droughts, and floods, can disrupt operations, reduce work hours, and even lead to fatalities.⁶ [Bolton et al. \(2020\)](#) also warn that climate change can shock the economy through labor supply. The current findings indicate that the relationship between climate change exposure and short-term debt usage is significant and positive for labor-intensive firms. The results of the cross-sectional subsample analysis support our hypothesis.

In addition to analyzing the relationship between climate change exposure and short-term debt usage, we consider the role of financial constraints. Financially unconstrained firms have more flexibility in choosing their debt maturity, whereas financially

⁶ The Samsung Electronics Texas factory serves as a pertinent example. In February 2021, a severe winter storm disrupted power supply and forced the factory to halt operations for several days ([Times, 2021](#)). This incident highlights the vulnerability of labor-intensive industries to climate change-related disruptions.

Table 5

Cross-sectional subsample analysis I: Sensitivity to climate change.

Panel A. Climate-sensitive industries				
	(1) <i>STDebt</i> _{<i>t</i>+1} Low Sensitivity	(2) <i>STDebt</i> _{<i>t</i>+1} High Sensitivity	(3) <i>STDebt</i> _{<i>t</i>+1} Low Sensitivity	(4) <i>STDebt</i> _{<i>t</i>+1} High Sensitivity
<i>CCEXP</i> _{<i>t</i>}	−0.005 (−0.808)	0.008*** (3.339)		
<i>CCEXP</i> ^{OP} _{<i>t</i>}			−0.003 (−0.173)	0.015*** (3.894)
Constant	0.747*** (19.384)	0.704*** (22.853)	0.745*** (19.381)	0.708*** (23.021)
Observations	16,534	23,757	16,534	23,757
Adjusted R ²	0.410	0.374	0.409	0.374
Controls	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel B. Labor intensity				
	(1) <i>STDebt</i> _{<i>t</i>+1} Low Labor Intensity	(2) <i>STDebt</i> _{<i>t</i>+1} High Labor Intensity	(3) <i>STDebt</i> _{<i>t</i>+1} Low Labor Intensity	(4) <i>STDebt</i> _{<i>t</i>+1} High Labor Intensity
<i>CCEXP</i> _{<i>t</i>}	0.004 (1.271)	0.008** (2.422)		
<i>CCEXP</i> ^{OP} _{<i>t</i>}			0.007 (1.371)	0.019*** (3.355)
Constant	0.778*** (22.927)	0.741*** (23.498)	0.779*** (23.045)	0.742*** (23.568)
Observations	20,150	20,141	20,150	20,141
Adjusted R ²	0.414	0.380	0.414	0.381
Controls	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of the cross-sectional subsample analysis using climate-sensitive industries and labor intensity. In Panel A, we define climate-sensitive industries as those likely to be adversely affected by climate change. Specifically, we consider firms belonging to agriculture, forestry, and fishing (SIC 01–09); mining (SIC 10–14); construction (SIC 15–17); and manufacturing (SIC 20–39) as climate-sensitive. This definition is based on previous reports. [Cho and Patten \(2007\)](#) and [Clarkson et al. \(2011\)](#) define environmentally sensitive industries as companies with primary SIC codes of 10 (mining), 13 (oil exploration), 26 (paper), 28 (chemical and allied products), 29 (petroleum refining), 33 (metals), and 49 (utilities). These industries are associated with polluting industries and have poorer environmental performance than others. In addition, [Bolton et al. \(2020\)](#) suggest that climate change can affect labor supply shock/food and other input shortages; thus, agriculture, forestry, and fishing (SIC 01–09); construction (SIC 15–17); etc., are included. In Panel B, *Labor Intensity* is measured using the median value of the number of employees divided by total assets. Although omitted from the table for brevity, the results include all control variables as shown in [Table 2](#). Detailed descriptions and data sources for other variables are provided in [Appendix A](#). All results are provided after controlling for industry- and fiscal-year fixed effects. The t-values based on standard errors clustered by the firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

constrained firms may struggle to access the long-term debt market during periods of high market uncertainty ([Datta et al., 2019](#)). Therefore, we hypothesize that the positive relationship between climate change exposure and short-term debt usage is more pronounced in financially constrained firms. To test this hypothesis, we use leverage ratio, credit rating, Altman's Z-score, and Tobin's Q-score as proxies for financial constraints.⁷ [Table 6](#) presents the results of our analysis and demonstrates that the relationship between climate change exposure and short-term debt usage is significant and positive for firms with high leverage ratios, lower credit ratings, and low Z- and Q-scores. These results are consistent with our hypothesis that financial constraints amplify the relationship between climate change exposure and short-term debt usage.

4. Conclusion

This study investigates the relationship between climate change exposure and a firm's preference for short-term debt. Leveraging a comprehensive dataset of U.S. firms spanning 2002 to 2020 and employing [Sautner et al.'s \(2023a\)](#) pioneering firm-level climate change exposure measure, this study aims to capture the nuanced and multifaceted nature of the climate risk faced by individual firms.

⁷ A sample is classified as "High credit rate" if the S&P Domestic Long-Term Issuer Credit Rating is in the range of AAA–BBB, and "Low credit rate" if the S&P Domestic Long-Term Issuer Credit Rating is in the range of BB+ or lower or unrated. The Z- and Q-scores are divided into high and low groups based on the median. The results are similar when the groups are divided at the threshold of 1.8 for the Z-score and 1 for the Q-score instead of using the median.

Table 6

Cross-sectional subsample analysis II: Financial constraints.

Panel A. Leverage ratio				
	(1) $STDebt1_{t+1}$ Low Leverage	(2) $STDebt1_{t+1}$ High Leverage	(3) $STDebt1_{t+1}$ Low Leverage	(4) $STDebt1_{t+1}$ High Leverage
$CCEXP_t$	0.002 (0.825)	0.007** (2.119)		
$CCEXP^{OP}_t$			0.005 (1.386)	0.017*** (3.121)
Constant	0.965*** (35.946)	0.286*** (11.399)	0.965*** (35.992)	0.288*** (11.486)
Observations	20,146	20,145	20,146	20,145
Adjusted R^2	0.402	0.147	0.402	0.149
Controls	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel B. S&P domestic long-term issuer credit rating				
	(1) $STDebt1_{t+1}$ Low credit rate	(2) $STDebt1_{t+1}$ High credit rate	(3) $STDebt1_{t+1}$ Low credit rate	(4) $STDebt1_{t+1}$ High credit rate
$CCEXP_t$	0.006** (2.339)	−0.001 (−0.224)		
$CCEXP^{OP}_t$			0.013*** (3.312)	0.001 (0.062)
Constant	0.763*** (30.355)	−0.222*** (−3.243)	0.765*** (30.467)	−0.223*** (−3.252)
Observations	34,839	5452	34,839	5452
Adjusted R^2	0.381	0.271	0.382	0.271
Controls	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel C. Altman Z score				
	(1) $STDebt1_{t+1}$ Low Z-score	(2) $STDebt1_{t+1}$ High Z-score	(3) $STDebt1_{t+1}$ Low Z-score	(4) $STDebt1_{t+1}$ High Z-score
$CCEXP_t$	0.006** (2.239)	0.002 (0.690)		
$CCEXP^{OP}_t$			0.012*** (2.746)	0.008 (1.600)
Constant	0.609*** (20.439)	0.818*** (25.899)	0.610*** (20.516)	0.818*** (25.972)
Observations	20,150	20,141	20,150	20,141
Adjusted R^2	0.367	0.399	0.367	0.399
Controls	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Panel D. Tobin Q				
	(1) $STDebt1_{t+1}$ Low Q-score	(2) $STDebt1_{t+1}$ High Q-score	(3) $STDebt1_{t+1}$ Low Q-score	(4) $STDebt1_{t+1}$ High Q-score
$CCEXP_t$	0.007** (2.404)	0.002 (0.912)		
$CCEXP^{OP}_t$			0.016*** (3.222)	0.008* (1.828)
Constant	0.772*** (23.115)	0.789*** (24.689)	0.773*** (23.166)	0.789*** (24.747)
Observations	19,106	19,093	19,106	19,093
Adjusted R^2	0.404	0.387	0.405	0.387
Controls	Yes	Yes	Yes	Yes
Ind FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: This table presents the results of the cross-sectional subsample analysis focusing on financial constraints. We use the leverage ratio, credit rating, Z-score, and Q-score as proxies for financial constraints. Although omitted from the table for brevity, the results include all the control variables, as shown in Table 2. Detailed descriptions and data sources for these variables are provided in Appendix A. All results are provided after

controlling for industry- and fiscal-year fixed effects. The t-values based on standard errors clustered by the firm are reported in parentheses. ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

Our analysis reveals that firms with high climate change exposure are more likely to utilize short-term debt, even after controlling for a range of factors influencing debt choices. Notably, opportunity-related climate change exposure emerges as a potent driver of short-term debt usage. Additionally, several robustness tests, including propensity score matching (PSM), an alternative measure, firm fixed effects, and Tobit analyses, further strengthen the robustness of our results. Furthermore, we find that the magnitude of this relationship intensifies within climate-sensitive and financially constrained firms.

Although the present study reveals important findings, it is important to acknowledge its limitations. First, although we examine the relationship between a climate risk at one point (t) and its short-term debt usage at a later point ($t + 1$) to account for strategic planning regarding future climate risks, there might be a reverse causality issue. For example, past climate-related damages may lead to a higher use of short-term debt at time $t + 1$, potentially distorting the results. Second, despite using PSM and various fixed effects to mitigate endogeneity concerns, a possibility of omitted variable bias remains. Unconsidered factors, such as hidden firm characteristics, could influence the relationship between short-term debt usage and climate change risk.

Despite these limitations, the findings have significant implications for businesses, investors, and policymakers. For firms, the findings suggest that climate change exposure is a factor to consider when making debt maturity decisions. For investors, the findings indicate that climate change exposure is a risk factor to consider when evaluating firms. For policymakers, the findings suggest that climate change policies have significant implications for debt markets.

CRedit authorship contribution statement

Sanghak Choi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Data availability

Data will be made available on request.

Appendix

Appendix A

Variable definitions.

Variables	Definitions	Database
<i>Panel A: Measures of short-term debt</i>		
<i>STDebt1</i>	The proportion of short-term debt within current liabilities (DLC) compared to the total debt (DLC + DLT).	Compustat
<i>STDebt2</i>	The proportion of debt comprising current liabilities (DLC) and debt maturing within 2 years (DD2) relative to the total debt (DLC + DLT).	Compustat
<i>STDebt3</i>	The proportion of debt comprising current liabilities (DLC) and debt maturing within 2 to 3 years (DD2 + DD3) compared to the total debt (DLC + DLT).	Compustat
<i>STDebt4</i>	The proportion of debt comprising current liabilities (DLC) and debt maturing within 2 to 4 years (DD2 + DD3 + DD4) relative to the total debt (DLC + DLT).	Compustat
<i>STDebt5</i>	The proportion of debt comprising current liabilities (DLC) and debt maturing within 2 to 5 years (DD2 + DD3 + DD4 + DD5) relative to the total debt (DLC + DLT).	Compustat
<i>Panel B: Measures of climate change exposure</i>		
<i>CCEXP</i>	The firm-level climate change exposure measure developed by Sautner et al. (2023a) employs a machine-learning approach. It assesses the relative frequency of climate change-related bigrams in corporate discussions during earnings conference calls. To enhance clarity, this variable is multiplied by 1000 for exposition, as suggested by Feng et al. (2022) .	Sautner et al. (2023a)
<i>CCEXP^{OP}</i>	Sautner et al.'s (2023a) opportunity-related climate change exposure measure. The relative frequency of bigrams captures opportunities related to climate change in corporate discussions during earnings conference calls. To enhance clarity, this variable is multiplied by 1000 for exposition, as suggested by Feng et al. (2022) .	Sautner et al. (2023a)
<i>CCEXP^{RG}</i>	Sautner et al.'s (2023a) regulatory-related climate change exposure measure. The relative frequency of bigrams captures regulatory aspects related to climate change in corporate discussions during earnings conference calls. To enhance clarity, this variable is multiplied by 1000 for exposition, as suggested by Feng et al. (2022) .	Sautner et al. (2023a)
<i>CCEXP^{PH}</i>	Sautner et al.'s (2023a) physical-related climate change exposure measure. The relative frequency of bigrams captures physical aspects related to climate change in corporate discussions during earnings conference calls. To enhance clarity, this variable is multiplied by 1000 for exposition, as suggested by Feng et al. (2022) .	Sautner et al. (2023a)
<i>Panel C: Control variables</i>		
<i>Size</i>	The natural logarithm of the total assets (AT).	Compustat
<i>Leverage</i>	The ratio of total liabilities comprising current liabilities (DLC) and long-term liabilities (DLTT) to the total assets (AT).	Compustat
<i>MTB</i>	The ratio of the market value of assets (CSHO * PRCC_F + AT - CEQ) to the total assets (AT).	Compustat / CRSP

(continued on next page)

Appendix A (continued)

Panel C: Control variables		
<i>AbEarn</i>	The ratio of the difference between the income before extraordinary items, adjusted for common stock equivalents (IBADJ) in year t and $t-1$, and the market value of equity ($PRCC_F * CSHPRI$).	Compustat /CRSP
<i>ATM</i>	The product of property, plant, and equipment over depreciation (PPEGT/DP) multiplied by the proportion of property, plant, and equipment in total assets (PPEGT/AT), plus the ratio of current assets to the cost of goods sold (ACT/COGS) multiplied by the proportion of current assets in total assets (ACT/AT).	Compustat
<i>ATV</i>	The standard deviation of daily stock returns over the fiscal year, multiplied by the market value of equity ($CSHO * PRCC_F$), divided by the market value of assets ($CSHO * PRCC_F + AT - CEQ$).	Compustat /CRSP
<i>R&D</i>	Research and development expenses (XRD) divided by the total assets (AT).	Compustat
<i>R&D dummy</i>	A dummy variable equal to one indicates that research and development expenses (XRD) are not reported, while a dummy variable equal to zero indicates otherwise.	Compustat
<i>AltmanZ</i>	3.3 times the ratio of earnings before interest and taxes to total assets (EBIT/AT), plus 0.99 times the ratio of total sales to total assets (SALE/AT), plus 0.6 times the ratio of market value of equity to total liabilities ($(CSHO * PRCC_F)/LT$), plus 1.2 times the ratio of current assets to total assets (ACT/AT), plus 1.4 times the ratio of retained earnings to total assets (RE/AT).	Compustat /CRSP
<i>TermPRM</i>	The variance in yield between 10-year and 6-month government bonds.	FRED

Appendix B

Additional robustness tests.

	(1) $STNP_{t+1}$	(2) $STNP_{t+1}$	(3) $STDebt1_{t+1}$	(4) $STDebt1_{t+1}$	(5) $STDebt1_{t+1}$	(6) $STDebt1_{t+1}$
$CCEXP_t$	0.003* (1.718)		0.004* (1.720)		0.006 (5.799)	
$CCEXP^{OP}_t$		0.007** (1.967)		0.005 (1.331)		0.013*** (7.091)
$Size_t$	-0.053*** (-26.045)	-0.054*** (-26.060)	-0.087*** (-16.075)	-0.087*** (-16.076)	-0.059*** (-50.927)	-0.059*** (-50.996)
$Leverage_t$	-0.342*** (-10.546)	-0.343*** (-10.556)	-0.196*** (-8.136)	-0.196*** (-8.142)	-0.409*** (-47.310)	-0.410*** (-47.399)
MTB_t	-0.005** (-2.019)	-0.005** (-2.021)	-0.011*** (-4.894)	-0.011*** (-4.880)	-0.005*** (-4.084)	-0.005*** (-4.070)
$AbEarn_t$	-0.017*** (-3.377)	-0.017*** (-3.373)	-0.018*** (-4.109)	-0.018*** (-4.111)	-0.028*** (-6.216)	-0.028*** (-6.209)
ATM_t	0.031 (1.209)	0.031 (1.214)	0.107*** (3.371)	0.107*** (3.377)	0.015 (0.887)	0.016 (0.900)
ATV_t	2.106*** (6.867)	2.102*** (6.862)	0.440* (1.934)	0.441* (1.935)	1.860*** (10.060)	1.851*** (10.018)
$R\&D_t$	0.189*** (3.199)	0.189*** (3.195)	0.083*** (3.432)	0.084*** (3.414)	0.155*** (12.621)	0.156*** (12.650)
$R\&D\ dummy_t$	0.041*** (4.261)	0.041*** (4.257)	0.001 (0.044)	0.001 (0.064)	0.048*** (8.309)	0.048*** (8.292)
$AltmanZ_t$	0.009*** (12.589)	0.009*** (12.591)	0.007*** (10.701)	0.007*** (10.695)	0.007*** (22.032)	0.007*** (22.054)
$TermPRM_t$	0.005 (0.689)	0.005 (0.670)	0.005 (0.775)	0.005 (0.779)	0.006 (0.855)	0.006 (0.816)
<i>Constant</i>	0.615*** (26.442)	0.616*** (26.518)	0.947*** (22.861)	0.948*** (22.912)	0.656*** (14.485)	0.660*** (14.573)
<i>Observations</i>	40,291	40,291	40,291	40,291	40,291	40,291
<i>Adjusted R²</i>	0.361	0.361	0.618	0.618		
<i>Pseudo R²</i>					0.365	0.365
<i>Firm FE</i>	No	No	Yes	Yes	No	No
<i>Ind FE</i>	Yes	Yes	No	No	Yes	Yes
<i>Year FE</i>	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents the results of the robustness tests. Columns 1 and 2 report the results using an alternative measure of short-term debt, $STNP$, defined as the ratio of debt in current liabilities without the current portion of long-term debt (NP) to total debt (DLC + DLT). Columns 3 and 4 show the regression results with firm fixed effects included. Columns 5 and 6 report the results from the Tobit regressions. Detailed descriptions and data sources for these variables are provided in Appendix A. All results are provided after controlling for industry- (firm-) and fiscal-year fixed effects in Columns 1, 2, 5, and 6, and for firm fixed effects in Columns 3 and 4. The t-values based on standard errors clustered by firm are reported in parentheses (except for Columns 5 and 6). ***, **, and * indicate significance at the 1 %, 5 %, and 10 % levels, respectively.

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