



Managerial perspectives on climate change and stock price crash risk

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ABSTRACT

In this study, we examine the effects of manager's perspectives on climate change on stock price crash risk. The analysis confirms that manager's climate change perspective is negatively associated with future stock price crash risk likelihood. Various channel tests show that investor attention and analyst coverage are potential channels through which a firm's climate change perspective improves financial stability and ultimately reduces crash risk. Our results are also robust to alternative climate change perspective measures.

1. Introduction

Unprecedented climate change not only affects our health, but also poses a significant risk to the economic and financial systems (Litterman et al., 2020). Limiting the global temperature rise at below 1.5 °C, as suggested by the Paris Agreement, has a significant effect on financial economics (Intergovernmental Panel on Climate Change, 2021). Physical climate change, such as global warming and sea level rise, may directly reduce a firm's productivity. Climate change may also indirectly affect a firm's costs due to governmental sanctions and regulations, such as the emission trading scheme. Simultaneously, some firms strategically use climate change issues as opportunities. For instance, firms associated with electric cars, renewable energy, emission reduction technologies, and environmentally friendly products are potential beneficiaries of climate change risks. As climate change risks do not unidirectionally affect firms, it is important to understand how firms and managers perceive climate change effects.

Firms' perceptions, especially managers' perspectives on climate change issues, are important because market participants play a critical role in price discovery and resource allocation. As business transformation accelerates in response to climate change, managers' perceived intentions and perspectives on such issues are highlighted. These perspectives are made public through earnings calls. Sautner et al. (2020) proposes a novel firm-level climate change perspective variable constructed from the transcripts of conference calls. They construct firm-level time-varying climate change perspective measures using machine learning methods. This measure counts the frequency of certain climate change bigrams in the earnings conference call transcripts and then divides the frequency by the total number of bigrams in the transcript.¹

Measuring the firm-specific climate change measure begins by defining the search set. The search set consists of words from past

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¹ For more detailed information regarding the variable construction, please refer to Sautner et al. (2020).

IPCC reports minus non-climate change words from Gutenberg dictionary. Sautner et al. (2020) then construct the reference set, a set of arbitrary chosen 50 general climate change bigrams, following which they partition the search set by sentences that include the reference set and those that do not. These sentences are statistically classified by machine learning classifiers, such as multinomial naïve Bayes, support vector machine and random forest, into groups that belong to a climate change-related group (search set that includes the reference set) or a non-related group (does not include reference set). Then, the grid search method is used to tune the hyper parameters. This process enables sentences that do not include the reference set bigrams to be included in the climate change-related group if the context is similar. The sum of the bigrams newly constructed by machine learning classifier and the initial 50 general climate change reference set give us a total of 3800 climate change-related bigrams. The reason for employing machine learning classification models is that they can train the context of climate change-related sentences and non-related sentences. The trained model can then be tested to distinguish sentences into a climate-change related or not-related set. Furthermore, models are flexible, that is, changing the threshold may increase or decrease the number of climate change related bigrams.

This study uses signaling theory to understand the effects of managerial perspectives of climate change. This theory argues that a firm's commitment to society or the environment may deliver a positive signal to the market (Spence, 1973; Karasek and Bryant, 2012; Liu et al., 2022). Their interest in environment and climate change ultimately translates into enhanced financial performance and a reduced risk of a stock price crash. Firms may use conference calls to demonstrate their opportunities with respect to climate change risks. This positive signal may not return immediate financial rewards but provides long-term advantages, especially with respect to enhanced competitiveness (Dhaliwal et al., 2011). Furthermore, a firm's stance on climate change may induce more public attention, which could also act as a monitoring mechanism (Feng et al., 2022). It improves a firm's information transparency and reduces agency costs, and consequently, reduces earnings management and lowers the likelihood of negative information being stockpiled (Rajgopal and Venkatachalam, 2011; Kim et al., 2012).

To test the effectiveness of managerial perspectives on specific climate changes, we further decompose climate change perspective measures into three different categories: opportunity, regulatory and physical effect views of climate change (Sautner et al., 2020). We find that the composition of climate change perspective has a significant effect on future stock price crash risk. Perspective measures with respect to opportunity, regulatory, and physical views of climate change have significant effects on reducing crash risk likelihood. The results imply that regardless of climate change topics, firms strategically use earnings call conferences to send a positive signal of environmental responsibility and financial stability, which results in a lower risk of a price crash (Liu et al., 2022).

Further channel tests show that the effects of climate change perspective on future crash risk manifest only when investor attention and analyst coverage are high. Some firms' climate change perspectives attract retail investors and financial institutions; these third parties monitor the firms' dubious behavior, ultimately reducing the likelihood of stock price crash risk.

The study makes significant contributions to the literature. First, it offers another potential determinant of the stock price crash risk. Kothari et al. (2009) argue that managers intentionally hide bad news to protect their positions, maintain their compensation packages, protect employment, and minimize potential litigation risks from the disclosure of negative news to the market. From this perspective, various studies postulate channels that strengthen this argument (Hutton et al., 2009; Kim et al., 2011a; Kim et al., 2011b; Kim et al., 2016; Li and Chan, 2016; Luo et al., 2016; Ni and Zhu, 2016; He et al., 2022; Yin et al., 2022). However, relatively little attention has been paid to how firm-level climate change perspective affects the risk of stock price crashes. This is mainly because of the difficulties in quantitatively measuring a firm's perspective level as unobserved heterogeneity exists across firms. Measuring context from corporate events such as conference calls may somewhat alleviate unobserved heterogeneity issue. In this manner, measures used in this study, which is directly calculated from the earnings calls, may be interpreted as capturing the managerial perspectives on climate change. This measure reflects the soft information originating from information exchanges between managers and financial institutions.

Thus, using a novel machine-learning-based measure, this study addresses this gap in the literature. Furthermore, it extends signaling theory by proposing the firm-level climate change perspective as another credible signal.

2. Data and methodology

2.1. Climate change exposure

Our data span from 2002 to 2020. For climate change perspective measures ($CCE_{i,t-1}$), we adopt the Sautner et al. (2020) dataset. Sautner et al. (2020) used machine learning methods to calculate the firm-level yearly climate change perspective using transcripts from earnings call conferences. The measures count the frequency of climate change bigrams in the transcript divided by the total number of bigrams. Authors name their variable "climate change exposure." Furthermore, the perspective measures are classified into three topic-based measures. For bigrams linked to development and opportunities such as "wind power" or "solar energy," we construct a climate change perspective measure related to opportunity ($CCE_OPP_{i,t-1}$); for bigrams related to risks such as "carbon tax" or "emission trading," we construct a perspective measure related to regulations ($CCE_REG_{i,t-1}$); and for word pairs intuitively linked to physical climate aspects such as "natural hazard" or "sea level," we construct a measure related to physical effects ($CCE_PHY_{i,t-1}$). For all perspective measures, a higher value indicates more mentions during the conference call.

2.2. Stock price crash risk

First, we measure the weekly returns for each firm and year. We define W as the firm-specific weekly return, computed as the

Table 1
Summary statistics of all variables.

Variables	Obs.	Mean	Std. Dev.	Skew.	Kurt.
CRASH _t	34799	0.28	0.45	0.98	1.96
NCSKEW _t	34799	0.16	1.16	0.37	4.91
DUVOL _t	34799	0.12	0.84	0.21	3.62
CCE _{t-1}	34799	0.09	0.25	6.65	64.04
DTURN _{t-1}	34799	0	0.2	1.5	530.1
NCSKEW _{t-1}	34799	0.12	1.13	0.41	4.96
SIGMA _{t-1}	34799	0.06	0.03	1.93	9.7
RET _{t-1}	34799	0	0.01	-0.44	7.21
SIZE _{t-1}	34799	6.21	2.08	0.29	2.99
MB _{t-1}	34799	2.02	1.74	6.98	134.49
LEV _{t-1}	34799	0.17	0.18	1.53	11.06
ROA _{t-1}	34799	0.07	0.21	-3.94	35.62
ACC _{t-1}	34799	0	0.49	5.3	887.18
RD _{t-1}	34799	0.05	0.12	7.41	167.04
RDD _{t-1}	34799	0.44	0.5	0.25	1.06
KURT _{t-1}	34799	2.55	3.74	3.35	19.69

Note. This table reports the descriptive statistics for the following control variables: stock turnover (*DTURN*_{*t*-1}), negative conditional skewness (*NCSKEW*_{*t*-1}), stock return volatility (*SIGMA*_{*t*-1}), firm specific average weekly return (*RET*_{*t*-1}), firm size (*SIZE*_{*t*-1}), market-to-book ratio (*MB*_{*t*-1}), leverage ratio (*LEV*_{*t*-1}), return on assets (*ROA*_{*t*-1}), earnings quality (*ACC*_{*t*-1}), R&D expenditure (*RD*_{*t*-1}), R&D missing dummy (*RDD*_{*t*-1}) and kurtosis (*KURT*_{*t*-1}). The period of the data is 2002–2020. We report observations, average, standard deviation, skewness and kurtosis of each variable.

natural log of one plus the residual return from the expanded market model regression. The market model regression is expressed as follows:

$$r_{j,\tau} = \alpha_j + \beta_{1,j}r_{m,\tau-2} + \beta_{2,j}r_{m,\tau-1} + \beta_{3,j}r_{m,\tau} + \beta_{4,j}r_{m,\tau+1} + \beta_{5,j}r_{m,\tau+2} + \varepsilon_{j,\tau}$$

where *r*_{*j*, τ} is the return on stock *j* in week τ , and *r*_{*m*, τ} is the return on the S&P500 index in week τ . The lead and lag terms for the S&P500 index return are included to allow for non-synchronous trading (Dimson, 1979). Further, the firm-specific weekly return for firm *j* in week τ , *W*_{*j*, τ} is computed as

$$W_{j,\tau} = \ln(1 + \varepsilon_{j,\tau})$$

Our first crash risk measure, *CRASH*_{*t*}, is defined as an indicator variable if any week in a given fiscal year for a given firm is the week when the firm’s weekly return falls below 3.09 standard deviations from the mean firm-specific returns over the entire fiscal year (Hutton et al., 2009). The second crash risk measure is negative conditional return skewness (*NCSKEW*). The *NCSKEW* of a firm in a fiscal year is calculated by taking the negative of the third moment of firm-specific weekly returns for each year and dividing it by the standard deviation of firm-specific weekly returns to the third power (Kim et al., 2011a), which is expressed as follows:

$$NCSKEW_{j,t} = - \left[n(n-1)^{3/2} \sum W_{j,\tau}^3 \right] / \left[(n-1)(n-2) \left(\sum W_{j,\tau}^2 \right)^{3/2} \right]$$

The last measure of stock price crash risk is the down-to-up volatility (*DUVOL*). For each firm *j* over a fiscal-year period *t*, we divide all the trading weeks into “down” and “up” weeks, with “down weeks” indicating the weeks when the firm-specific weekly returns are below the annual mean and “up weeks” indicating those when the firm-specific weekly returns are above the annual mean. Furthermore, we calculate the standard deviation for each group. The *DUVOL* variable is calculated as the log of the ratio of the standard deviation for the “down weeks” to the standard deviation for the “up weeks.” This is formally expressed as follows:

$$DUVOL_{j,t} = \log \left\{ \left[(n_u - 1) \sum_{DOWN} W_{j,\tau}^2 \right] / \left[(n_d - 1) \sum_{UP} W_{j,\tau}^2 \right] \right\}$$

where *n*_{*u*} and *n*_{*d*} denote the number of “up” and “down” weeks, respectively, during the fiscal year *t*. Higher values indicate higher crash risk likelihood.

2.3. Other variables

We also include the following lagged variables to control for potential unobserved heterogeneity (Chen et al., 2001): stock turnover (*DTURN*_{*t*-1}), negative conditional skewness (*NCSKEW*_{*t*-1}), stock return volatility (*SIGMA*_{*t*-1}), firm-specific average weekly return (*RET*_{*t*-1}), firm size (*SIZE*_{*t*-1}), market-to-book ratio (*MB*_{*t*-1}), leverage ratio (*LEV*_{*t*-1}), return on assets (*ROA*_{*t*-1}), earnings quality (*ACC*_{*t*-1}), R&D expenditure (*RD*_{*t*-1}), missing R&D dummy (*RDD*_{*t*-1}), and kurtosis (*KURT*_{*t*-1}). Weekly measures such as *SIGMA*_{*t*-1} and *RET*_{*t*-1} are scaled over the fiscal year so that the frequency of all measures is calculated at a yearly basis. We include firm and year fixed effects to further alleviate endogeneity concerns. Furthermore, we control for industry effects as being a prominent industry

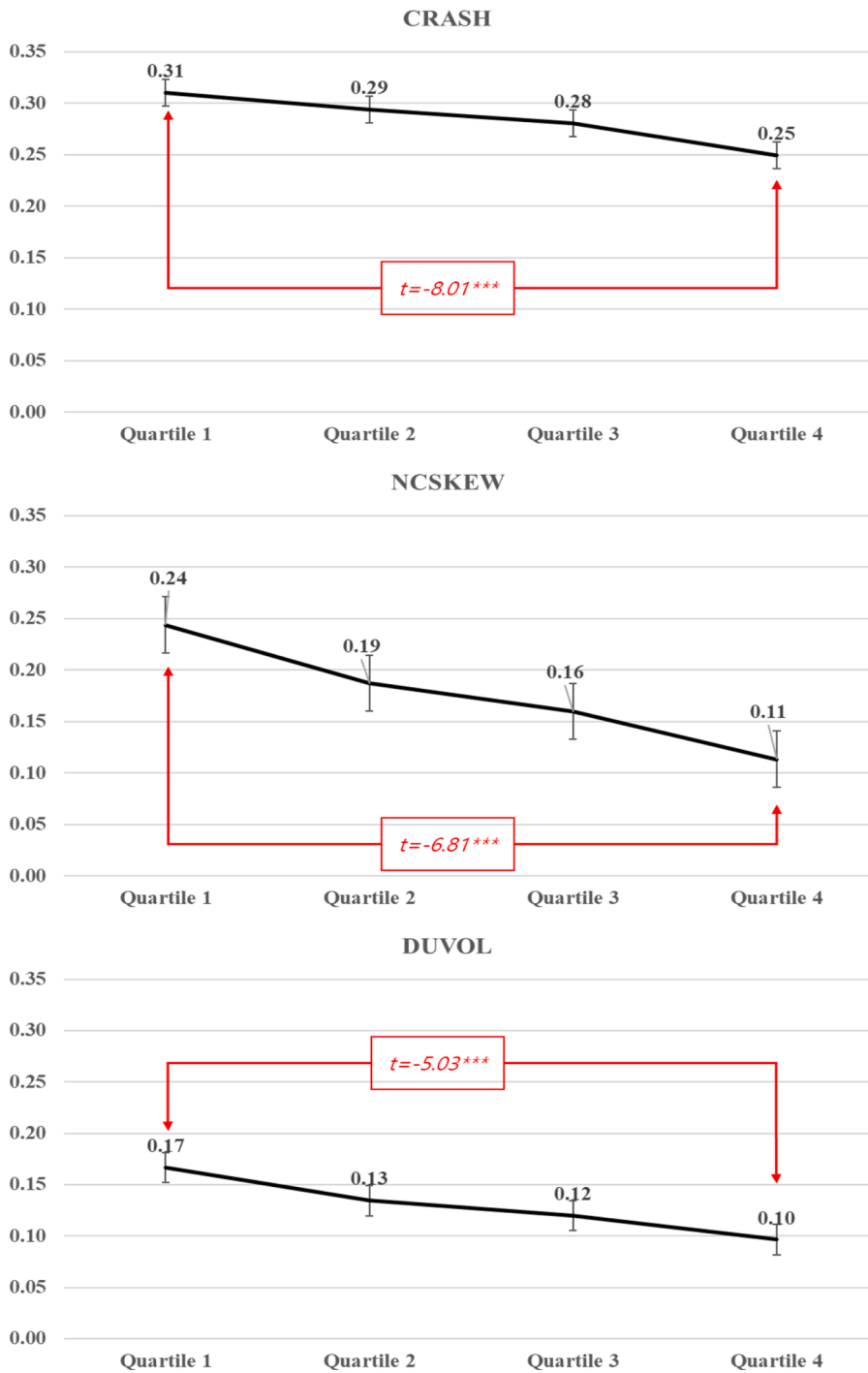


Fig. 1. Change of crash risk measures with respect to climate change perspective level, Note. Fig. 1 illustrates change in stock price crash risk measures with respect to change in climate change perspective. Quartile 1 is a group of firms with the bottom 25% with a climate change perspective measure, and quartile 4 is a group of firms with the top 25% with a climate change perspective measure. We also report t-statistics comparing the crash risk values of bottom quartile climate change perspective group to top quartile climate change perspective group. *** indicate significance at 1% levels.

Table 2
Main results.

Variables	(1) $CRASH_t$	(2) $NCSKEW_t$	(3) $DUVOL_t$	(4) $CRASH_t$	(5) $NCSKEW_t$	(6) $DUVOL_t$
CCE_{t-1}	-0.358*** (0.004)	-0.169*** (0.003)	-0.143*** (0.000)	-0.369*** (0.003)	-0.174*** (0.002)	-0.146*** (0.000)
$DTURN_{t-1}$	0.077 (0.312)	0.115*** (0.003)	0.093*** (0.001)	0.076 (0.319)	0.114*** (0.003)	0.091*** (0.001)
$NCSKEW_{t-1}$	-0.129*** (0.000)	-0.091*** (0.000)	-0.048*** (0.000)	-0.132*** (0.000)	-0.092*** (0.000)	-0.048*** (0.000)
$SIGMA_{t-1}$	-2.811*** (0.001)	-2.823*** (0.000)	-2.375*** (0.000)	-2.722*** (0.002)	-2.804*** (0.000)	-2.365*** (0.000)
RET_{t-1}	-2.822 (0.222)	5.344*** (0.000)	6.583*** (0.000)	-2.876 (0.216)	5.490*** (0.000)	6.739*** (0.000)
$SIZE_{t-1}$	0.509*** (0.000)	0.462*** (0.000)	0.381*** (0.000)	0.506*** (0.000)	0.462*** (0.000)	0.382*** (0.000)
MB_{t-1}	0.094*** (0.000)	0.122*** (0.000)	0.101*** (0.000)	0.092*** (0.000)	0.122*** (0.000)	0.101*** (0.000)
LEV_{t-1}	0.012 (0.944)	-0.187** (0.020)	-0.214*** (0.000)	-0.010 (0.952)	-0.186** (0.022)	-0.211*** (0.000)
ROA_{t-1}	1.148*** (0.000)	0.463*** (0.000)	0.259*** (0.000)	1.121*** (0.000)	0.444*** (0.000)	0.246*** (0.000)
ACC_{t-1}	0.032 (0.487)	0.029 (0.174)	0.029* (0.056)	0.033 (0.475)	0.033 (0.130)	0.031** (0.046)
RD_{t-1}	1.241*** (0.000)	0.316** (0.023)	0.224** (0.025)	1.216*** (0.000)	0.297** (0.033)	0.211** (0.035)
RDD_{t-1}	-0.004 (0.974)	0.050 (0.372)	0.050 (0.220)	-0.012 (0.914)	0.060 (0.294)	0.051 (0.213)
$KURT_{t-1}$	-0.003 (0.554)	0.004 (0.123)	0.005*** (0.003)	-0.003 (0.542)	0.003 (0.135)	0.005*** (0.004)
Constant		-2.742*** (0.000)	-2.334*** (0.000)		-2.745*** (0.000)	-2.339*** (0.000)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	No	No	No	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,522	28,160	28,160	25,265	27,884	27,884
Pseudo R ²	0.0285			0.0286		
Adjusted R ²		0.063	0.070		0.063	0.070

Note. This table reports the baseline regression results. The dependent variable in Columns (1) and (4) is the variable indicating whether the firm experienced a weekly average significant stock price drop, $CRASH_t$, the dependent variable in Column (2) and (5) is a negative coefficient of skewness, $NCSKEW_t$, and the dependent variable in Column (3) and (6) is the down-to-up volatility measure of the crash likelihood, $DUVOL_t$. Regression results commonly include control variables as well as firm and year fixed effects. P-values based on standard errors clustered by firm and year are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

strongly related to climate change may also drive results.

3. Results

3.1. Univariate and multivariate analysis results

Table 1 reports the descriptive statistics of the variables. We find that the statistics of climate change perspective measures, stock price crash risk measures, and other control variables are similar to those of prior studies on climate change perspective (Heo, 2021) or stock price crash risk (Habib et al., 2018).

Fig. 1 illustrates the changes in stock price crash risk measures with respect to changes in climate change perspective. Quartile 1 is the group of firms with the bottom 25% of climate change perspective, and Quartile 4 is the group of firms with the top 25% of climate change perspective. We also report t-statistics comparing the crash risk values of the bottom quartile climate change perspective group to those of the top quartile climate change perspective group. Note that as climate change perspective increases, all stock price crash risk measures decrease unidirectionally. The t-statistics are also statistically significant.

However, interpreting univariate analysis may be biased due to endogeneity. Thus, we employ multivariate pooled ordinary least squares estimation with various control variables and fixed effects to examine climate change perspective effects. The model is specified as follows:

$$CRASH_VARS_{j,t} = \beta_0 + \beta_1 CCE_{j,t-1} + \gamma' CONTROLS_{j,t-1} + \varepsilon_{j,t},$$

where $CRASH_VARS_{j,t}$ indicates the three crash risk variables used in the model: $CRASH_{j,t}$, $NCSKEW_{j,t}$, and $DUVOL_{j,t}$. $CCE_{j,t-1}$ indicates climate change perspective variables and $CONTROLS_{j,t-1}$ indicates the set of control variables used in the main regression.

Table 2 presents the baseline regression results. Columns (1) – (3) report the results for $CRASH_{j,t}$, $NCSKEW_{j,t}$, and $DUVOL_{j,t}$ for firm and year fixed effects. Columns (4) – (6) show the results for industry fixed effects included. Note that, regardless of the stock price crash risk measures, we find a statistically significant negative association between climate change perspective and stock price crash risk measures. The findings also support signaling theory in that the climate change perspective delivers a credible signal and attracts investors. This ultimately increases a firm's financial stability, which reduces stock price crash risk. Further to the baseline regression, we also employ system GMM test, and the results were significant indicating that endogeneity issues are somewhat washed out.²

² These results are unreported in the paper.

Table 3
Channel tests.

Panel A. Investor attention effect						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	High attention $CRASH_t$	Low attention $CRASH_t$	High attention $NCSKEW_t$	Low attention $NCSKEW_t$	High attention $DUVOL_t$	Low attention $DUVOL_t$
CCE_{t-1}	-0.484* (0.090)	0.087 (0.749)	-0.197* (0.100)	-0.141 (0.192)	-0.153* (0.081)	-0.158** (0.043)
Constant			-4.905*** (0.000)	-2.481*** (0.000)	-4.130*** (0.000)	-1.982*** (0.000)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8411	7502	10,280	9819	10,280	9819
Pseudo R ²	0.0383	0.0596				
Adjusted R ²			0.099	0.109	0.107	0.120
Panel B. Analyst coverage effect						
	(1)	(2)	(3)	(4)	(5)	(6)
Variables	High Coverage $CRASH_t$	Low Coverage $CRASH_t$	High Coverage $NCSKEW_t$	Low Coverage $NCSKEW_t$	High Coverage $DUVOL_t$	Low Coverage $DUVOL_t$
CCE_{t-1}	-0.614** (0.039)	-0.197 (0.265)	-0.244** (0.031)	-0.128 (0.117)	-0.198** (0.017)	-0.103* (0.079)
Constant			-3.859*** (0.000)	-2.535*** (0.000)	-3.545*** (0.000)	-2.149*** (0.000)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8038	12,703	9346	14,816	9346	14,816
Pseudo R ²	0.0329	0.0399				
Adjusted R ²			0.069	0.075	0.078	0.082

Note. This table reports the channel test results where we use investor attention and analyst coverage as potential channels to explain the relationship between the climate change perspective and the future stock price crash risk. Columns (1), (3) and (5) provide regression results on $CRASH_t$, $NCSKEW_t$ and $DUVOL_t$ for firms with high investor attention, respectively. Columns (2), (4) and (6) show results for firms with low investor attention. For the attention measure, we use average values of 10-K report views (Panel A of Table 3) and analyst coverage values (Panel B of Table 3) as a threshold value. Regression results commonly include control variables as well as firm and year fixed effects. P-values are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 4
Alternative climate change perspective measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variables	Opportunity $CRASH_t$	$NCSKEW_t$	$DUVOL_t$	Regulatory $CRASH_t$	$NCSKEW_t$	$DUVOL_t$	Physical $CRASH_t$	$NCSKEW_t$	$DUVOL_t$
$CCE_{OPP,t-1}$	-0.555** (0.012)	-0.229** (0.022)	-0.180** (0.012)						
$CCE_{REG,t-1}$				-1.231 (0.163)	-0.883** (0.022)	-0.917*** (0.001)			
$CCE_{PHY,t-1}$							-3.080 (0.169)	-1.745* (0.084)	-1.433** (0.048)
Constant		-2.750*** (0.000)	-2.341*** (0.000)		-2.753*** (0.000)	-2.342*** (0.000)		-2.753*** (0.000)	-2.343*** (0.000)
Firm-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	25,522	28,160	28,160	25,522	28,160	28,160	25,522	28,160	28,160
Pseudo R ²	0.0284			0.0282			0.0282		
Adjusted R ²		0.063	0.069		0.063	0.070		0.063	0.069

Note. This table reports the regression results for alternative climate change perspective measures. Columns (1) – (3) provide regression results for climate change perspective related to opportunity on $CRASH_t$, $NCSKEW_t$, and $DUVOL_t$ respectively; Columns (4) – (6) show regression results for regulatory related climate change perspective effects on $CRASH_t$, $NCSKEW_t$, and $DUVOL_t$ respectively; and Columns (7) – (9) provide regression results for physical climate change related perspectives on $CRASH_t$, $NCSKEW_t$, and $DUVOL_t$ respectively. Regression results commonly include control variables as well as firm and year fixed effects. T-values based on standard errors clustered by firm and year are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

3.2. Underlying mechanism between climate change perspective and stock price crash risk

We conduct various channel tests to understand the underlying mechanism between climate change perspective and crash risk. If a firm's climate change perspective attracts retail or institutional investors and takes a monitoring role to reduce crash risk, then the relationship between climate change perspective and future stock price crash risk should manifest if the firm is highly attractive to investors. We employ subsample analysis to test the channel. We group firms according to whether they are highly attractive or not. For the attention measure, we use the average values of 10-K report views (Panel A of Table 3) and analyst coverage values (Panel B of Table 3) as threshold values.

Table 3 presents the results. Panel A provides the results for investor attention as calculated by 10-K report views, and Panel B reports the results for analyst coverage. Columns (1)–(3) show the results for the high-attention firms. Note that the relationship between climate change perspective and stock price crash risk manifests only when firm attention is high. Thus, a firm's tendency to withhold negative information is reduced when a higher volume of investors and analysts monitor the firm's climate change perspective. These results also complement prior findings that external monitoring significantly reduces stock price crash risk (Xu et al., 2013; Kim et al., 2014; Kim et al., 2019; He et al., 2019; Wen et al., 2019).

Finally, we breakdown the climate change perspective measure into opportunity, regulatory, and physical views. If climate change-related perspective is a significant factor that reduces a firm's crash risk likelihood, then different categories of climate change should unidirectionally affect crash risk. Table 4 presents the results, and confirm the hypothesis that climate change perspective, regardless of measurement method, is a statistically significant factor that improves a firm's financial stability and reduces stock price crash risk likelihood.

4. Conclusion

This study shows that firm-level climate change perspective may have a positive effect on reducing a firm's crash risk likelihood. Using climate change perspective calculated from earnings call transcripts, we suggest that a higher perspective of global climate change issues attracts the attention of external parties such as investors and financial analysts, whose monitoring reduces a firm's negative information withholding behavior. Our study provides strong evidence supporting signaling theory and offer practical contributions for a firm's sustainable development.

CRedit authorship contribution statement

Hail Jung: Conceptualization, Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Visualization. **Chang-Keun Song:** Conceptualization, Investigation, Resources, Writing – review & editing, Supervision, Project administration, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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