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ORIGINAL ARTICLE

Attention to climate change and downside risk: Evidence from China

Xing Chen[1] | **Xian Chen**[1] | **Longhao Xu**[1] | **Fenghua Wen**[1,2]

[1]School of Business, Central South University, Changsha, Hunan, China

[2]School of Finance, Shanghai Lixin University of Accounting and Finance, Shanghai, China

Correspondence
Longhao Xu and Fenghua Wen, School of Business, Central South University, Changsha, Hunan, China.
Email: xulonghao@csu.edu.cn; wfh@amss.ac.cn

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Abstract
We explore the role of public climate attention, captured by the Baidu search volume index, in the downside risk. Using 45 keywords from five perspectives related to climate change, we construct a public climate attention index in China. We find a positive and significant relationship between climate attention and downside risk at the market-level and firm-level. Moreover, the risk-increase effect of climate attention becomes more prominent for state-owned and high-carbon-emission firms. Further analysis shows that excellent sustainable performance can moderate the adverse effect of rising climate attention, while the major climate disasters exacerbate the effect. Overall, our findings shed additional light on the important role of collective climate beliefs in corporate risk management and investor decision-making.

KEYWORDS
climate attention, climate disasters, downside risk, ESG performance, risk management

1 | INTRODUCTION

In recent decades, public opinion on the existence and severity of climate change has significantly increased. According to a recent survey from the Yale Program on Climate Change Communication, which has been tracking levels of concern since 2008, 70% of Americans (which is an all-time high) are worried about climate change (Howe et al., 2015). However, forming accurate beliefs about long-term events, such as climate change, will impose an enormous information burden on participants (Herrnstadt & Muehlegger, 2014). Growing climate beliefs increase global concern on the impact of climate change on the broader economy, particularly in the capital market, bringing climate concern into their investment decisions to reduce potential losses.

Crucially, as climate change is an extreme event, investors should not only consider the average expected losses, but more importantly, the outliers, especially extreme scenarios (Economist Intelligence Unit, 2015). Downside risk explains the worst-case scenario in which investors and firms can suffer, which means sharp declines in asset values (Sautner & Starks, 2021). Identifying and estimating downside risk is rapidly becoming key in corporate risk management and investor asset allocation (Reber, 2017). Although several studies have explored the relationship between climate beliefs and the capital market (Baldauf et al., 2020; Ilhan et al., 2021; Painter, 2020), they do not examine the impact of climate beliefs on corporate and investor risk management, especially for extreme downside risks. Therefore, we aim to fill this gap by answering the following question: Does collective attention to climate change affect firms' downside risk?

On the one hand, public climate attention may be more likely to accumulate firms' downside risk. First, an increase in climate attention will raise stock price volatility. For example, investors tend to prevent the impact of climate change on their portfolio by selling carbon-intensive stocks or buying green stocks, respectively (Choi et al., 2020; El Ouadghiri et al., 2021), increasing uncertainty in future yields. Second, when collective climate attention increases, financial institutions begin pricing climate risk in their loans and credit ratings, increasing the financing costs of firms, leading to increased future downside risk. Furthermore, high climate attention increases the probability of adopting pro-climate policies. Large uncertainties characterize pro-climate policies considering their impact on firm profitability, as such policies represent larger deviations from current practices (Ilhan et al., 2021). Third, public climate attention, considered an important factor related to firm-level climate change exposure (Sautner et al., 2020), increases the exposure cost of firms' climate risk. Greater climate attention increases investors' sensitivity to climate shocks in their portfolios, with firms facing greater consequences of climate risk exposure. Therefore, enhancing climate attention will increase the downside risk of firms in the future.

On the other hand, participation is crucial for investors to mitigate climate risks (Economist Intelligence Unit, 2015). Institutional investors consider climate risk engagement with their portfolio firms instead of divestment as a better approach to managing climate risk (Krueger et al., 2020). When public climate attention increases, firms need to take action to mitigate climate risks and improve their sustainability under shareholders' pressure, decreasing downside risk. Additionally, increasing collective climate attention tends to wake up firms' environmental responsibility. Better environmental policies can help firms lower capital costs and increase value (El Ghoul et al., 2018), while downside risk decreases (Hoepner et al., 2018). Therefore, the increased climate attention will reduce firms' potential downside risks. The above analysis indicates that the effect of climate attention on firm downside risk is ultimately an empirical issue addressed in this study.

Notably, China provides an appropriate setting to study collective climate attention and downside risk. First, China is among the countries suffering the most adverse effects of climate change.[1] Many firms face direct costs and risks related to climate change and, hence, have a great impact on the capital market. Second, China has a unique economic environment, the world's largest emerging development market. Statistics report that the total market value of China's stock market reached 79.72 trillion RMB by the end of 2020.[2] Exploring factors affecting downside risk of firms is beneficial for systemic or financial stability. Finally, as the largest carbon-emitting country globally (Looney, 2020), China has adopted a set of measures to actively respond to climate change, such as optimizing energy structure, improving energy efficiency, and promoting the carbon market construction.[3] These measures will inevitably affect corporate regulation policy and future development directions.

Public attention is often dynamic, situational, or temporary (Ripberger, 2011). Although traditional survey-based measures can reveal attitudes through inquiries, respondents often lack sufficient incentive to answer questions carefully or truthfully (Singer, 2002). While changes in media coverage provide a useful proxy for public climate attention, it remains a more indirect measurement, with an unclear causal relationship with public attention.[4] Therefore, this study proposes a more direct measure of public climate attention by using the aggregate search volume index (SVI). Specifically, we collect the Baidu daily SVI of 45 keywords such as "*climate change*," "*global warming*," and "*carbon dioxide*" from five different categories related to climate change: broad cognitive level, opportunity attention, regulatory attention, physical attention, and climate frontier conferences. Then to avoid dimensional disasters and information overlap, we apply factor analysis (FA) to extract and construct climate attention index (*Atten*) based on the statistical correlations from the keywords at the monthly level.

We first relate the climate attention index to market-level downside risk, which is measured in two ways. The first measure is the value at risk (*VaR*), capturing the maximum loss of a stock with a given probability. As a second measure, we calculate the lower partial moment (*LPM*), which captures the distributions of negative returns during the measurement period. Considering Shanghai composite index (CSI) to represent the Chinese stock market, we show that climate attention has an economically and statistically positive effect on downside risk in months t and $t+1$. However, the risk-increase effect of attention is temporary and dissipates in the month $t+2$. We find similar results among other representative stock indexes.

Then, we examine the relationship between climate attention and downside risk at the firm-level. We find that climate attention still positively influences firm-level downside risk, measured by *VaR* and *LPM*. A one-standard-deviation increase in attention (*Atten*) corresponds to an increase of approximately 14.3% (6.2%) standard deviation of *VaR* (*LPM*). Our findings remain valid after using alternative proxy variables of climate attention and downside risk, and considering high-degree fixed effects and different subsamples. These findings support the view that firms are confronted with higher stock price volatility, higher exposure costs to climate risk, and lower profitability when public awareness of climate change increases, thus increasing firm-level downside risks.

High-carbon-emission firms tend to be more sensitive to increased climate attention as they are confronted with greater financial risks, and tighter environmental regulatory risks, or socially responsible investors avoid holding their stocks. Our results show that climate attention has a stronger impact on the downside risk for high-emission firms. Additionally, state-owned enterprises (SOEs) are a distinctive feature of the Chinese securities market. Because of their close relationship with state governments, SOEs are more likely to receive timely assistance from the state when affected by extreme events (Zhang et al., 2010). Therefore, despite increased public climate concern, SOEs are less likely to respond to this variation, hence less likely to reduce their climate risks actively. This study finds that the risk-increase effect of climate attention is more prominent in SOEs.

We further investigate the role of environmental, social, and governance (ESG) performance in the relationship between climate attention and firm-level downside risk. ESG assessment can comprehensively evaluate firms' ability to

[1] Reference "Enhance Actions on Climate Change: China's intended national Determined Contributions, 2015". See http://www.china.org.cn/chinese/2015-07/01/content_35953590.htm

[2] Reference Shenzhen Stock Exchange, see http://www.szse.cn/market/overview/index.html.

[3] Reference "China's Policies and Actions to Address Climate Change: 2020 Annual Report".

[4] Ripberger (2011) finds public attention to health care might precede media coverage, whereas attention to terrorism or global warming appears to parallel or even lag media coverage.

deal with long-term risks such as climate risks. Firms with better ESG performance can better adapt to climate change and address climate risks, leading to decreased downside risk. This conjecture is borne in the data. We find that firms with excellent sustainable performance can alleviate the adverse effects of rising climate concerns.

Finally, as attention is limited (Kahneman, 1973), people are more inclined to focus on personal experiences and attention-grabbing extreme events. To the extent that the public is more concerned about climate issues as recent exposure to major climate disasters, corporate downside risks should be greater. Results show that the salience effects of climate attention on downside risks are indeed enhanced when major disasters occur. After excluding firm-month observations directly affected by climate disasters and considering disaster economic damage, our results remain robust, highlighting that public climate beliefs are constantly updated, and extreme climate disasters can exacerbate the risk-increase effect of climate attention.

Our study contributes to two strands of literature. Nascent literature focuses on the impact of climate attention on the capital market. Bernstein et al. (2019) and Baldauf et al. (2020) show that climate change beliefs affect house prices, which are projected to be underwater, selling at a discount. Painter (2020) argues that climate attention can increase the issuance costs of long-term municipal bonds issued by climate-affected countries. The prices of climate-derived products also reflect the update of climate beliefs of agents in the weather market (Schlenker & Taylor, 2021). On the investor side, institutional investors deem that climate risks have important financial implications for their portfolios (Krueger et al., 2020). Choi et al. (2020) further show that retail investors revise their climate beliefs under abnormal warm weather, while Ramelli et al. (2021) study the effect of climate activism. In this line of research, El Ouadghiri et al. (2021) find that public attention to climate change can positively affect the future returns of U.S. sustainability stock indices. Although some literature studies climate attention and asset price, research about climate attention and downside risk is limited. Our analyses help to provide insights into the real relation between public climate attention and corporate and investor risk management.

Additionally, our study adds to the literature on the determinants of downside risks. Relevant factors for downside risks include ESG participation and disclosure (Hoepner et al., 2018; Reber et al., 2021), environment performance (Muhammad et al., 2015), initial return, post-issue liquidity (Reber, 2017), family involvement (Alessandri et al., 2018), corporate governance characteristics such as executive ownership, and independent boards (Wang et al., 2015). Most literature is based on the firm's characteristics, with few studying downside risks from collective beliefs about climate change: whether climate attention affects the company's future downside risk, and how it affects remain vague. In this paper, we propose a possible answer for this important question.

2 | DATA AND SUMMARY STATISTICS

2.1 | Measures

To examine the relationship between public climate attention and firm-level downside risks, we obtain all Chinese A-share listed firms from January 2011 through December 2020.[5] We use three filters to process our data. First, we exclude financial service firms for their markedly different disclosure requirements and accounting rules in this regulated industry. Second, we exclude firms listed on the stock exchange for less than 1 year considering we are unable to assess the veracity of financial reporting data in these firms. Third, we exclude the firm-month observations with missing values for the control variables. To alleviate the influence of extreme values, we winsorize continuous variables at the 1 and 99% levels. Our final sample contains 282,866 firm-month observations of 3615 listed firms.

2.1.1 | Climate attention

With Da et al. (2011) and Drake et al. (2012) using the Google search index as a proxy indicator of investor attention to indicate investor demand or sentiment, growing studies use search data to express public attention to climate change.[6] Compared with traditional measures, searching for keywords represents the level of knowledge regarding the topic (Lineman et al., 2015). Internet search data can also collect data from underrepresented groups more effectively, avoiding sample bias (Manzano & Ura, 2013). More critically, search measures exposed and dynamic attention: if someone searches for terms about climate change, there is no doubt that he is paying attention to it.[7]

Given the variety of search engines in China, Figure 1 shows that the Baidu search engine is always the mainstream search platform, with a market share of about 70% after 2014.[8] More importantly, similar to Google trend, Baidu also provides Baidu trends, the weighted sum of the search volumes of certain keywords.[9] Therefore, we choose the Baidu search volume index of search keywords related to climate change to construct public climate attention.

We tend to capture climate attention from five perspectives: broad cognitive level, physical attention, regulatory attention, opportunity attention, and climate frontier conferences. First, as most literature do (Lang, 2014; Lineman et al., 2015), we capture broadly-defined climate change aspects as

[5] Our sample started in 2011 because the Baidu search volume index, including both PC terminal and mobile terminal search volume, started in 2011.
[6] For example, Choi et al. (2020) select the "global warming" search index to measure public climate beliefs. El Ouadghiri et al. (2021) use the "climate change" keyword search index to measure public attention.
[7] Additionally, although searching keywords such as "climate change" do not necessarily represent climate believers—and may even include the search activities of climate skeptics—the search volume index can still provide useful trends information as we are interested in public climate attention instead of the belief differences.
[8] The data comes from the website: http://gs.statcounter.com.
[9] The Baidu trend website is https://index.baidu.com/v2/index.html#/.

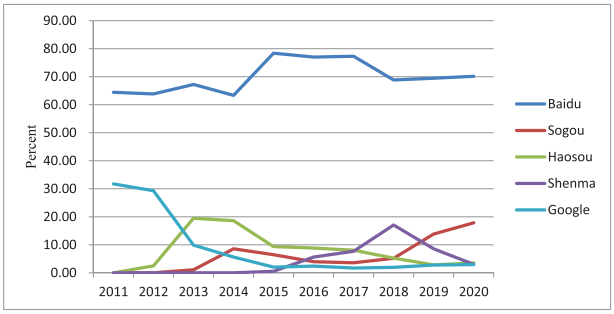

FIGURE 1 The Chinese search engine market share. This figure presents the most popular search engines in China from 2011 to 2020

people are most likely to search keywords such as "*climate change*," and "*global warming*" in Chinese to know about climate change.[10] Second, we focus on the attention to physical shocks caused by climate change. Due to climate change, some firms face direct costs originating from extreme weather events or rising sea levels. The public is also affected by physical shocks to climate change. Examples include extreme weather events, such as high temperatures and coastal flooding, generating attention to climate change (Deryugina, 2013; Sisco et al., 2017). Third, we capture the attention to the policy and regulatory shocks due to climate change. Effectively combating climate change is a major policy challenge. Policies and regulations related to climate change have adverse effects on certain companies, such as fossil fuel firms (Delis et al., 2019), through carbon pricing or limiting emissions. The public search data of regulatory shocks also reflects the level of awareness of climate change. Fourth, simultaneously, climate change does provide some opportunities for firms and investors. Climate change promotes technological innovation for climate mitigation and brings new investment opportunities, such as renewable energy or energy storage (Sautner et al., 2020). Hence, we focus on the attention to opportunity shocks due to climate change. Finally, we capture attention to climate frontier conferences as international climate conferences can affect the loan rates and credit ratings of polluting companies (Delis et al., 2019; Seltzer et al., 2020). Climate conferences can also help the public better understand the knowledge about climate change and the latest concerted actions for fighting climate change.

Due to the interdependence and interaction among the five perspectives of climate attention, where each dimension has its own unique meaning as well as each indicator within the dimensions, directly assigning weights to measure public attention will affect the estimation accuracy. Therefore, we adopt the factor analysis (FA) to avoid dimensional disasters and information overlap, which expresses five dimensions of climate attention with several unrelated common factors, and construct the climate attention monthly by calculating the comprehensive factor scores. Specifically, we construct the public climate attention index as follows:

First, based on the above five perspectives, we construct keyword lists made up of 45 keywords. The details of the keywords are reported in Appendix B. After manually collecting the daily SVI of the 45 keywords, we calculate the monthly average value by each. Second, we apply factor analysis, specifically the principal-component factor method, to estimate the loading matrix of 45 keywords, and we use varimax rotation to the loading matrix of the factor solution for improving the overall interpretability (Kaiser, 1958).[11] Third, we retain eight common factors according to the Kaiser criterion and calculate the factor scores respectively.[12] Then, we take the comprehensive factor score, which equals the cumulative sum of the contribution rate of each common factor multiplied by the factor score, to measure the climate attention. Finally, we note that there is a variation in climate attention across months of the year. Specifically, attention is higher in April and October than in January and July every year. For example, the average of climate attention is 0.28 in April and is −0.42 in January. To remove the influence of potential month-of-year effects, we make seasonal adjustments by calculating the mean value of attention plus residuals from the regression of the monthly attention on month dummies. We use this adjusted value as our main measure of climate attention (*Atten*).

2.1.2 | Downside risk

We construct two indicators that are widely used to measuring downside risk following Hoepner et al. (2018). We obtain the daily return on individual stocks, including dividend payments from the CSMAR. As the first measure, value at risk (*VaR*) is calculated as the bottom 5th percentile of the daily returns during a month, which usually corresponds to the worst return outcome. We then take the absolute value of *VaR* to ensure that higher *VaR* values correspond to higher levels of downside risk. Our second measure of downside risk is the second-order lower partial moment (*LPM*), which is calculated as the square root of the semi-variance below zero (Bawa & Lindenberg, 1977). For firm i in month t, this measure is defined as

$$LPM = \sqrt{\frac{1}{N_1 - 1} \sum_{i=1}^{N_1} \left(r_{n,i} - \bar{r}_{n,i}\right)^2}$$

where N_1 is the number of observations of negative returns for firm i in month t, $r_{n,i}$ is the negative return on firm i and $\bar{r}_{n,i}$ is the mean value of $r_{n,i}$.

[10] Milfont (2012) and Shi et al. (2015) show greater climate-related knowledge has a positive impact on public concern about climate change and global warming.

[11] The principal-component factor method (PCF) in Stata runs the factor analysis but rescales the estimates to conform to a standard principal component analysis (PCA). With blending factor analysis and PCA, PCF not only follows the basic principles of PCA but also allows to conduct analysis limited to factor analysis (e.g., factor rotation). For more details about this approach, see Mooi et al. (2018).

[12] The Kaiser criterion is an analytical approach for determining the number of factors. factors with eigenvalue ≥1 will be retained as the selection criteria (Kaiser, 1960). There are two popular approaches to computing factor scores, the Regression method and the Bartlett method. We choose to rely on the regression method in this paper.

Additionally, we use *VaR5* (*VaR1*) and *ES5* (*ES1*) as robust proxies following Atilgan et al. (2020). Specifically, we calculate *VaR5* (*VaR1)* as the 5th (1st) percentile of daily returns from the past year to the end of month *t* with the requirement of at least 200 nonmissing return observations.[13] Expected shortfall (*ES*), proposed by Artzner et al. (1999), is another popular proxy of downside risk. It measures the conditional expected loss beyond the VaR threshold. We calculate *ES5* (*ES1*) as the average losses of stock *i* that are less than or equal to the 5th (1st) percentile of the daily returns from the past year to the end of month *t* with the requirement of at least 200 nonmissing return observations. We use the absolute values of *VaR5* (*VaR1)* and *ES5* (*ES1*).

2.1.3 | Carbon emission

Following Zhang and Wang (2021), we manually match the eight energy- and carbon-intensive industries, namely, petrochemical, chemical, building materials, steel, nonferrous metals, paper, electric power, and aviation, with the industry classification standard issued by the China Securities Regulatory Commission (CSRC) in 2012. A total of 593 firms in the matched industries are classified as high-emission firms, while others are classified as low-emission firms.

2.1.4 | ESG performance

The mainstream social responsibility ratings internationally include MSCI, Bloomberg, and Sustainalytics. Owing to the limited sample of Chinese listed companies included, we choose the following indicators to measure the ESG performance of firms based on China's corporate rating system. First, we obtain the Huazheng ESG rating from WIND, which measures a firm's sustainable performance quarterly on a scale of CCC to AAA.[14] Companies with better sustainable performance rank higher. We define firms with an ESG rating of A or higher as firms with excellent sustainable performance. Second, we obtain Hexun's corporate social responsibility (CSR) rating scores from its official website[15]. The better the firm's sustainable performance, the higher the social responsibility score. We defined firms with excellent sustainable performance are those with scores higher than the median of the same industry in the same year. We also cross-check our results with the Bloomberg ESG score covered with 1121 listed firms.

2.1.5 | Climate disaster

Climate disaster data are obtained from the CSMAR event database, which collects all climate disasters occurring in China from 2014 to 2020, including typhoons, floods, droughts, rainfall, and low temperatures. For each disaster, CSMAR reports the start and end dates, city and area codes, direct economic damage value, and the number of deaths. To ensure that a climate disaster has a material impact on public perception of climate change, we consider disasters with a direct economic loss of above 6 billion RMB (adjusted for inflation of 2019). This filtering procedure leaves us with 30 major disasters. The total economic damages caused by the major disasters account for more than 60% of the losses in our entire disaster sample. We define the dummy variable *Disaster* that equals one if extreme climate disasters occur in month *t*. Appendix D1 reports the detail about the 30 major climate disasters that we study. We also calculate the total economic losses (*Damage*) that occurred each month as a robust proxy with no limit to the major disasters.

2.1.6 | Stock and company information

The firm-specific characteristic variables and industry information are available from CSMAR. Because the main variables we are interested in, climate attention and downside risks, are monthly data, we set firm characteristic variables to monthly specifications by assigning the last quarterly accounting data for each month within the quarter. For the details of variable definitions, see Appendix A1.

2.2 | Summary statistics

Table 1 represents our final sample distribution by industry (Panel A) and by year (Panel B), respectively. The manufacturing industry is the main component of the sample, accounting for 62%, followed by the information transmission industry. In contrast, the industry of resident service, repair, and other services occupies the smallest proportion, with no more than 0.1%. Compared with the industry distribution, the sample size in each year is relatively stable, with an upward trend in general. It indicates the rapid expansion of China's stock market in the past 10 years.

We present the descriptive statistic of our main variables in Table 2. Panel A reports summary statistics. The mean value of *VaR* (*LPM*) is 4.173 (1.597), with a standard deviation of 2.302 (0.843). The mean value and standard deviation of *Atten* are 0.029 and 0.242, respectively. Panel B presents the Pearson's correlation coefficients for the variables. There is a significantly positive correlation between climate attention and downside risk. Some firm characteristic variables also correlate with downside risk. Specifically, smaller and younger firms, firms with worse profitability and less investment have higher downside risk.

[13] The past year specifically refers to the past 250 trading days.

[14] Huazheng ESG rating not only covers almost all A-share listed firms, but also adds indicators suitable for China's national conditions, such as poverty alleviation and CSRC (China Securities Regulatory Commission) penalties. Based on the three dimensions of environment, society, and corporate governance, Huazheng ESG rating is further divided into 14 themes and 26 key indicators.

[15] Hexun CSR is one of the main measurements for the social responsibility of China's listed firms, made up of five dimensions: shareholder responsibility, employee responsibility, supplier, client and consumer responsibility, environmental responsibility, and social responsibility respectively. The data is manually collected from http://stockdata.stock.hexun.com/zrbg/.

TABLE 1 Sample distribution

Panel A: Full sample distribution by industry				Panel B: Full sample distribution by year		
Industry		**Freq.**	**Percent**	**Year**	**Freq.**	**Percent**
A	Transport, storage and postal service	9,224	3.26	2011	19,590	6.93
B	Accommodation and catering	922	0.33	2012	23,554	8.33
C	Industry of information transmission, software and information technology services	20,881	7.38	2013	25,661	9.07
D	Agriculture, forestry, animal husbandry and fishery	3,845	1.36	2014	24,584	8.69
E	Manufacturing	176,575	62.42	2015	22,439	7.93
F	Health and social work	1,090	0.39	2016	26,222	9.27
G	Industry of resident service, repair and other services	24	0.01	2017	30,191	10.67
H	Construction	7,530	2.66	2018	36,223	12.81
I	Real estate	12,354	4.37	2019	40,023	14.15
J	Wholesale and retail	14,970	5.29	2020	34,379	12.15
K	Education	754	0.27			
L	Industry of culture, sports and entertainment	4,055	1.43			
M	Water conservancy, environment and public facility management industry	4,400	1.56			
N	Industry of electric power, heat, gas and water production and supply	10,591	3.74			
O	Scientific research and technical service industry	2,483	0.88			
P	Leasing and commercial services	4,176	1.48			
Q	Diversified industries	1,626	0.57			
R	Mining	7,366	2.60			
	Total	282,866	100.00	Total	282,866	100.00

Note: Panel A reports the distribution of firm-month observations by industry. Panel B presents the sample distribution by year.

3 | RESULTS AT MARKET LEVEL

To provide initial evidence on the effect of climate attention on firm downside risks, we first explore the relationship between climate attention and downside risks at the aggregate market-level.[16]

$$Down\ side\ \ risk_{i,t+k} = \beta_0\ + \beta_1\ \times Atten_t\ \ +\ \gamma Controls_{i,t}\ +\ \mu_{i,t+k} \tag{1}$$

where $Downside\ risk_{i,t+k}$ denotes stock index i's *VaR* and *LPM* in month t+k. In this paper, we choose to test downside risk of the Shanghai composite index (CSI), which was issued by Shanghai stock exchanges in July 1991, comprehensively reflecting the general situation and operation of overall stock price changes in the Shanghai security market. $Atten_t$ measures the public climate attention in month t, which is our main interest variable. Following Da et al. (2015), control variables consist of the CBOE China ETF Volatility Index (*VIX*), changes in newspaper-based economic policy uncertainty for China (*EPU*), business confidence (*BC*), and changes in macro prosperity coincident index (*MP*).[17]

Panel A of Table 3 reports the regression results for our baseline model. Columns (1– 3) capture downside risk measured by *VaR*, and columns (4–6) capture downside risk measured by *LPM*. Regardless of the proxies, however, there is an economically sizeable and strong positive association between public climate attention and downside risks of the aggregate stock market, significant at the 1% level. In economic terms, for example, the estimate in column (1) shows that a one-standard-deviation increase in climate attention translates into an increase of 16.7% standard deviation in downside risk.[18] Moreover, we also verify that the effect of climate attention is temporary: the coefficients remain significant when $k = 1$ but reverse when $k = 2$.

We examine some other representative stock indexes. Panel B focuses on the price trend of A share in the Shenzhen stock market. Panel C focuses on small and medium enterprise stock index. The stock index tested is Shenzhen component index (Panel B), SME composite index

[16] In addition, considering our key independent variable, climate attention, is measured at the aggregate level, running panel regressions of firm downside risk on an aggregate measure of climate attention can inflate our t-statistics due to cross-sectional correlation among firms. Therefore, we test the relationship at the stock market-level first. We are grateful to the anonymous referee for making this suggestion.

[17] Business confidence and macro prosperity index are calculated from The National Bureau of Statistics of China. Both of the data are available at https://www.ceicdata.com. CBOE China ETF Volatility Index is available at https://fred.stlouisfed.org. EPU indices in our analysis are developed by Davis et al. (2019), which are available at https://www.policyuncertainty.com/china_epu.html.

[18] The standard deviation of downside risk for SCI is 1.437, and the standard deviation of attention is 0.249 in the table unreported. Therefore, the economic impact can be calculated as $0.249 \times 0.964/1.437 = 0.167$.

TABLE 2 Descriptive statistics and correlations

Panel A: Summary statistics

	Mean (1)	SD (2)	p25 (3)	Median (4)	p75 (5)	Num (6)
VaR_{t+1}	4.173	2.302	2.524	3.569	5.120	282,866
LPM_{t+1}	1.597	0.843	0.973	1.394	2.036	282,866
$Atten_t$	0.029	0.242	−0.165	0.042	0.207	282,866
MTB_t	3.931	3.964	1.763	2.780	4.562	282,866
$Size_t$	15.618	0.936	14.941	15.488	16.156	282,866
$Freefloat_t$	0.772	0.254	0.578	0.874	1.000	282,866
$Leverage_t$	0.426	0.212	0.253	0.418	0.585	282,866
ROA_t	0.025	0.035	0.005	0.018	0.040	282,866
Invest_t	0.030	0.035	0.006	0.017	0.040	282,866
$Profit_t$	0.080	0.183	0.021	0.073	0.152	282,866
$Dividend_t$	0.816	1.123	0.000	0.407	1.129	282,866
Age_t	10.733	7.172	4.000	9.000	17.000	282,866

Panel B: Correlation matrix

		1	2	3	4	5	6	7	8	9	10	11	12
1	VaR_{t+1}	1.00											
2	LPM_{t+1}	0.89*	1.00										
3	$Atten_t$	0.10*	0.09*	1.00									
4	MTB_t	0.15*	0.14*	0.00	1.00								
5	$Size_t$	−0.02*	−0.03*	0.17*	0.09*	1.00							
6	$Freefloat_t$	−0.06*	−0.07*	0.06*	−0.10*	0.06*	1.00						
7	$Leverage_t$	−0.04*	−0.06*	−0.03*	0.00	0.13*	0.28*	1.00					
8	ROA_t	−0.05*	−0.05*	−0.03*	0.07*	0.25*	−0.17*	−0.33*	1.00				
9	$Invest_t$	−0.01*	−0.01*	−0.12*	0.01*	0.01*	−0.17*	−0.08*	0.27*	1.00			
10	$Profit_t$	−0.06*	−0.06*	−0.01*	−0.05*	0.23*	−0.13*	−0.29*	0.63*	0.09*	1.00		
11	$Dividend_t$	−0.16*	−0.16*	0.00	−0.21*	0.21*	0.01*	−0.04*	0.29*	0.01*	0.26*	1.00	
12	Age_t	−0.08*	−0.09*	0.11*	−0.06*	0.16*	0.52*	0.36*	−0.16*	−0.21*	−0.11*	0.01*	1.00

Note: This table reports descriptive statistics for a full sample of 282,866 firm-month observations over the 2011–2020 period. Panel A presents the summary statistics including public climate attention, firm-level downside risks, and control variables. Panel B presents the Pearson's correlation coefficients.
*Indicates statistical significance at 1% levels. Definitions for each variable can be found in Appendix A.

(Panel C). Consistent with our previous results, the estimated coefficients remain positive and significant for both stock indexes, suggesting climate attention can still have a powerful but temporary effect on market-level downside risks.

Overall, rising public climate attention can increase the downside risk of the overall stock market, which provides preliminary evidence for subsequent research on downside risks at the firm-level.

4 | RESULTS AT FIRM LEVEL

4.1 | Regression design

To investigate the association between climate attention and firm-level downside risk, we estimate the following model by using the monthly firm-level panel regression:

$$Downside\ risk_{i,t+1} = \alpha + \beta \times Atten_t + \gamma Controls_{i,t} + Industry + Year + \mu_{i,t} \quad (2)$$

where Downside risk is proxied by $VaR_{i,t+1}$ and $LPM_{i,t+1}$ for firm i in month $t+1$. Our primary explanatory variable is $Atten_t$, measuring the public climate attention in month t. The explained variables are one month forward of all explanatory variables, allowing us to test whether climate attention can affect the future downside risks of firms.

We include controls that may influence firm-level downside risks. First, firms with larger sizes, more growth opportunities, better operating performance and profitability can better sustain negative economic shocks. Accordingly, we control for firm market value (*Size*), market-to-book ratio

TABLE 3 Public climate attention and market-level downside risk

Panel A: Attention and downside risk of Shanghai composite index

	VaR_t (1)	VaR_{t+1} (2)	VaR_{t+2} (3)	LPM_t (4)	LPM_{t+1} (5)	LPM_{t+2} (6)
$Atten_t$	0.9636**	0.9956*	0.1666	0.5259***	0.2909	0.1313
	(0.4655)	(0.5220)	(0.5406)	(0.1798)	(0.1826)	(0.1934)
VIX_t	0.1125***	0.0676***	0.0377*	0.0408***	0.0224**	0.0170**
	(0.0275)	(0.0235)	(0.0203)	(0.0107)	(0.0091)	(0.0082)
EPU_t	−0.0010	−0.0009	0.0006	−0.0004	−0.0004	0.0003
	(0.0010)	(0.0013)	(0.0015)	(0.0005)	(0.0005)	(0.0006)
BC_t	−0.0838**	−0.0241	0.0030	−0.0357**	−0.0067	0.0084
	(0.0403)	(0.0542)	(0.0528)	(0.0161)	(0.0236)	(0.0232)
MP_t	−0.1065	−0.2731	−0.3024	−0.0710*	−0.1216	−0.1474
	(0.1137)	(0.1915)	(0.2064)	(0.0375)	(0.0914)	(0.1029)
_cons	−0.9545	0.2087	0.9852*	−0.2912	0.1973	0.3382*
	(0.6327)	(0.5579)	(0.5018)	(0.2486)	(0.2148)	(0.1994)
Observations	116	115	114	116	115	114
Adjusted R^2	0.3310	0.1094	0.0122	0.3288	0.0769	0.0256

Panel B: Attention and downside risk of SZSE component index

	VaR_t (1)	VaR_{t+1} (2)	VaR_{t+2} (3)	LPM_t (4)	LPM_{t+1} (5)	LPM_{t+2} (6)
$Atten_t$	1.2785**	1.4286**	0.4240	0.6021***	0.4984**	0.2677
	(0.5208)	(0.5558)	(0.6087)	(0.1864)	(0.1995)	(0.2192)
Controls	YES	YES	YES	YES	YES	YES
Observations	116	115	114	116	115	114
Adjusted R^2	0.3527	0.1810	0.0261	0.3305	0.1369	0.0346

Panel C: Attention and downside risk of SME composite index

	VaR_t (1)	VaR_{t+1} (2)	VaR_{t+2} (3)	LPM_t (4)	LPM_{t+1} (5)	LPM_{t+2} (6)
$Atten_t$	1.2938**	1.6000***	0.3974	0.4528**	0.4703**	0.1160
	(0.5118)	(0.5509)	(0.6177)	(0.1891)	(0.1978)	(0.2165)
Controls	YES	YES	YES	YES	YES	YES
Observations	116	115	114	116	115	114
Adjusted R^2	0.3523	0.1996	0.0400	0.3322	0.1751	0.0642

Note: This table estimates the effects of public climate attention at month t on the downside risk of Shanghai composite index (Panel A), SZSE component index (Panel B) and SME composite index (Panel C) at month t+k, respectively. The dependent variable in columns (1)-(3) is value at risk at bottom 5th percentile (*VaR*) of each stock index. In columns (4)-(6), the dependent variable is the second-order lower partial moment (*LPM*). The main independent variable is climate attention (*Atten*), which is constructed based on the Baidu search index of 45 climate related keywords (see the detail of construction in 2.1 part). The sample period covers January 2011 through December 2020. Standard errors for coefficients, robust to heteroscedasticity and autocorrelations, are reported in parentheses. ***, **, and * represent statistical significance at 1%, 5%, 10% levels, respectively. Definitions for each variable can be found in Appendix 1.

(*MTB*), return on assets (*ROA*), and profit margin (*Profit*). Leverage may affect the downside risk of equity returns (Bhandari, 1988). Thus, we control for firm leverage (*Leverage*). Listed age (*Age*), investment rate (*Invest*), dividend ratio (*Dividend*), and free-float ratio (*Freefloat*) are also included. Second, we include industry and year fixed effects allowing us to control for time-invariant differences among industries and differences across time. Specifically, the year fixed effect can control changes in public attention toward climate change, average Internet penetration rate, and composition of Internet users over time, while the industry fixed effect can control certain changes in industry policy. Further, we cluster standard errors at the firm-level to reduce potential cross-sectional dependence.

4.2 | Regression results

The regression results on the effect of climate attention on downside risk are reported in Table 4. Columns (1) and (3) present results included the industry and year fixed effects, but without control variables. Coefficient estimates on *Atten* are 1.388 and 0.222 for the downside risk measured by *VaR* and *LPM*, respectively. Columns (2) and (4) report similar results after including the control variables. The coefficients on *Atten* are 1.364 and 0.217, respectively, which are significant at the 1% confidence level. This effect is economically significant. The coefficient estimate in column (2) indicates that a one-standard-deviation increase in climate attention corresponds to an increase of 14.3% (= 1.364 × 0.242/2.302)

TABLE 4 Public climate attention and firm-level downside risk

	VaR_{t+1} (1)	VaR_{t+1} (2)	LPM_{t+1} (3)	LPM_{t+1} (4)
$Atten_t$	1.388***	1.364***	0.222***	0.217***
	(0.028)	(0.028)	(0.010)	(0.010)
MTB_t		0.046***		0.016***
		(0.003)		(0.001)
$Size_t$		−0.025**		−0.032***
		(0.011)		(0.004)
$Freefloat_t$		−0.363***		−0.135***
		(0.030)		(0.011)
$Leverage_t$		−0.290***		−0.121***
		(0.041)		(0.015)
ROA_t		−2.125***		−0.727***
		(0.233)		(0.089)
$Invest_t$		−0.585***		−0.122*
		(0.178)		(0.067)
$Profit_t$		−0.149***		−0.039**
		(0.047)		(0.017)
$Dividend_t$		−0.205***		−0.074***
		(0.006)		(0.002)
Age_t		−0.017***		−0.007***
		(0.001)		(0.001)
$Constant_t$	4.133***	5.181***	1.590***	2.348***
	(0.010)	(0.159)	(0.004)	(0.058)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	282,866	282,866	282,866	282,866
Adjusted R^2	0.163	0.191	0.145	0.175

Note: This table reports the regression results of public climate attention at month *t* on downside risk at month *t+1*. The dependent variable in columns (1) and (2) is value at risk at bottom 5th percentile (*VaR*). In columns (3) and (4), the dependent variable is the second-order lower partial moment (*LPM*). The main independent variable is climate attention (*Atten*), which is constructed based on the Baidu search index of 45 climate related keywords (see the detail of construction in Section 2.1). The sample is from January 2011 to December 2020. Standard errors for coefficients are clustered by firm and reported in parentheses. ***, **, and * represent statistical significance at 1, 5, 10% levels, respectively. Definitions for each variable can be found in Appendix A.

standard deviation of *VaR*. The coefficient estimate in column (4) shows a one-standard-deviation increase in climate attention is associated with an increase corresponding to 6.2% (= 0.217 × 0.242/0.843) of the standard deviation of *LPM*. To sum up, the empirical analysis in Table 4 suggests higher climate attention is associated significantly with higher firm downside risk in the future.

4.3 | Robust test

4.3.1 | Alternative measures

In this subsection, we run several robustness tests by using alternative measures of our main variables. First, we use *VaR5* (*VaR1*) and *ES5* (*ES1*), the value at risk and expected shortfall at the 5th (1st) percentile following Atilgan et al. (2020), as proxy variables for firm-level downside risk. In Table 5, we present the estimation results. *Atten* remains positive and significant at the 1% level, although its magnitude decreases slightly compared with those in columns (1) and (2) of Table 4, suggesting that our main findings are valid.

Second, we note the sharp increase in market share of the Baidu search engine over the 2014–2015 period. Concurrently, China's stock market boomed. Referring to Da et al. (2011), we do a detrend by subtracting the average attention during the previous 12 months as a proxy measure of climate attention to further avoid potential time-related correlations. The results remain prominent and are shown in Appendix C1. Furthermore, we reconstruct public climate attention by selecting the top three and top six keywords most searched in each category, resulting in 15 and 30 keywords, respectively. The results of our main analysis remain unchanged.[19]

4.3.2 | Other robust tests

To further ascertain the robustness of our results, several additional tests are conducted. Table 6 presents the results of the estimation. In Panel A, we re-estimate the main regression under different fixed-effect models to alleviate the omitted variable bias. Columns (1) and (2) consider the firm-fixed effect to mitigate potential problems possibly caused by omitting time-invariant firm-specific characteristics. We further control for potential omitted variables by introducing high-degree fixed effects into the model. Columns (3) and (4) include the industry-year fixed effect to control for variables omitted from the time-variant industry level. Columns (5) and (6) further introduce province-year fixed effects to control for the influence of time-variant macrolevel factors. Our estimation results show that our main findings are unlikely brought about by company-specific omitted characteristics, time-variant industry levels, or macrolevel omitted variables.

In Panel B, we conduct several tests to ensure our main findings are not merely driven by certain subsamples and model specifications. Columns (1) and (2) exclude ST and ST* stock samples as firms with delisting warnings may have greater downside risk. At the end of 2017, China officially launched carbon emissions trading (CET) as an important measure for tackling climate change. Hence, downside risks in polluting industries and public attention are likely to increase. Therefore, in columns (3) and (4), we use subsamples from 2011–2017 to avoid the impact of CET policy. Institutional investors are inclined to reduce downside risk by restraining firms from hoarding bad news, with a large proportion of institutional investors believing that climate change is happening (Krueger et al., 2020). Therefore, we additionally introduce institutional investors' shareholdings (*InstuHold*) in columns (5) and (6) to address the

[19] For simplicity, the results are not reported, but they are available from the authors upon request.

TABLE 5 Alternative measures of downside risk

	$VaR1_{t+1}$ (1)	$VaR5_{t+1}$ (2)	$ES1_{t+1}$ (3)	$ES5_{t+1}$ (4)
$Atten_t$	0.342***	0.882***	0.158***	0.636***
	(0.014)	(0.013)	(0.012)	(0.011)
MTB_t	0.035***	0.044***	0.021***	0.040***
	(0.004)	(0.003)	(0.004)	(0.003)
$Size_t$	−0.296***	−0.221***	−0.256***	−0.249***
	(0.016)	(0.010)	(0.015)	(0.012)
$Freefloat_t$	−0.667***	−0.483***	−0.590***	−0.588***
	(0.047)	(0.032)	(0.043)	(0.037)
$Leverage_t$	−0.271***	−0.131***	−0.242***	−0.203***
	(0.066)	(0.046)	(0.061)	(0.052)
ROA_t	−2.713***	−1.867***	−2.142***	−2.397***
	(0.320)	(0.233)	(0.298)	(0.259)
$Invest_t$	−0.787***	−0.738***	−0.636***	−0.818***
	(0.270)	(0.193)	(0.242)	(0.219)
$Profit_t$	−0.021	−0.249***	0.099	−0.133**
	(0.068)	(0.049)	(0.065)	(0.055)
$Dividend_t$	−0.258***	−0.174***	−0.226***	−0.216***
	(0.010)	(0.007)	(0.010)	(0.008)
Age_t	−0.028***	−0.019***	−0.022***	−0.024***
	(0.002)	(0.001)	(0.002)	(0.002)
$Constant_t$	13.204***	8.769***	13.186***	11.001***
	(0.232)	(0.149)	(0.219)	(0.183)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	282,866	282,866	282,866	282,866
Adjusted R^2	0.363	0.499	0.341	0.482

Note: This table reports the results of regression of public climate attention at month t on downside risk measured by alternative variables at month t+1. The dependent variable in columns (1–2) is value at risk, the 5th (1st) percentile of daily returns of stock i in the past year following Atilgan et al. (2020). In columns (3–4), the dependent variable is expected shortfall, the average losses of stock i that are less than or equal to the 5th (1st) percentile of the daily returns in the past year. The main independent variable is climate attention (*Atten*), which is constructed based on the Baidu search index of 45 climate related keywords (see the detail of construction in Section 2.1). The sample is from January 2011 to December 2020. Standard errors for coefficients are clustered by firm and reported in parentheses. ***, **, and * represent statistical significance at 1, 5, 10% levels, respectively. Definitions for each variable can be found in Appendix A.

issue that institutional investors can have an impact on climate attention and firm-level downside risks simultaneously. Our results from the main analysis remain valid for these specifications.

Overall, using the different model specifications above, the association between public climate attention and future downside risk is still consistent with our main results.

4.4 | Cross-sectional variations on firms

This section focuses on the cross-sectional differences in corporate aspects that characterize our sample.

4.4.1 | High- versus low-emission firms

High-emission firms tend to be more sensitive to climate attention, as their future profitability is adversely affected by greater financial risks and tighter environmental regulatory risks.[20] Furthermore, people may update their valuation of high-emission firms when climate attention is updated. Motivated by profit-seeking or risk aversion, investors may sell the stocks or postpone investment of high-emission firms to think that climate change hurts firms' future cash flow and increases future emission costs. Additionally, socially responsible investors may tend to avoid holding high-emission stocks considered "sin stocks." Therefore, we expect that high-emission firms are subject to greater pressure from increased climate attention and thus face greater downside risks.

To test the heterogeneity effects of climate attention on the different types of carbon-emitting firms, we divide our sample into two groups—high-carbon emission firms and low-carbon emission firms—according to whether the firm's subindustry implements carbon trading. Table 7 reports the estimation results. The *Atten* coefficients in all columns are positive and significant. This indicates that climate attention can increase the downside risk of both high-emission and low-emission firms. The coefficient difference tests show that among high-emission firms, the risk-increase effect of attention represented is more prominent than that of low-emission firms. Our finding is consistent with the evidence in Ilhan et al. (2021), showing that for carbon-intensive firms, the cost of protection against downside tail risk is magnified at times when public attention to climate change spikes.

4.4.2 | SOEs versus non-SOEs

Ownership type may impact the positive relationship between climate attention and downside risk. State-owned enterprises (SOEs) will not focus on maximizing profits because the state has both political and economic objectives. Corporate performance in such firms will be inferior owing to weaker governance arrangements (Estrin & Perotin, 1991). Meanwhile, because of their close relationship with the government, SOEs can receive timely assistance from the state when affected by extreme negative events (Wang et al., 2008). Therefore, even when faced with increased climate attention, SOEs may be less likely to care about market reactions compared with non-SOEs, owing to their lack of sufficient incentives and crisis awareness to reduce firms' climate risks actively. Moreover, because of the special status of SOEs in the Chinese market, investors may demand SOEs to take

[20] For example, Seltzer et al. (2020) find firms with poor environmental profiles have lower credit ratings and higher yield spreads. Fossil fuel firms exposed to stricter climate policies are faced with higher costs of credit after the Paris Agreement (Delis et al., 2019). Bolton and Kacperczyk (2021) find that investors demand higher premium compensation for their exposure to the emission risks of high-emission companies.

TABLE 6 Additional robust tests

Panel A: High-degree fixed effects

	VaR_{t+1} (1)	LPM_{t+1} (2)	VaR_{t+1} (3)	LPM_{t+1} (4)	VaR_{t+1} (5)	LPM_{t+1} (6)
$Atten_t$	1.318***	0.201***	1.363***	0.216***	1.362***	0.216***
	(0.028)	(0.010)	(0.028)	(0.010)	(0.028)	(0.010)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	No	No	No	No
Year FE	Yes	Yes	No	No	No	No
Industry*year FE	No	No	Yes	Yes	Yes	Yes
Province*year FE	No	No	No	No	Yes	Yes
Observations	282,850	282,850	282,866	282,866	282,866	282,866
Adjusted R^2	0.227	0.213	0.194	0.178	0.196	0.180

Panel B: Specific subsamples and alternative model specifications

	Exclude ST/ST* firm		Subsample in 2011–2017		Controlling for *InstuHold*	
	VaR_{t+1} (1)	LPM_{t+1} (2)	VaR_{t+1} (3)	LPM_{t+1} (4)	VaR_{t+1} (5)	LPM_{t+1} (6)
$Atten_t$	1.351***	0.212***	3.933***	1.127***	1.363***	0.216***
	(0.029)	(0.011)	(0.032)	(0.012)	(0.028)	(0.010)
$InstuHold_t$					−0.320***	−0.120***
					(0.038)	(0.014)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	266,722	266,722	172,241	172,241	282,577	282,577
Adjusted R^2	0.193	0.177	0.302	0.278	0.192	0.176

Note: This table reports the results of regression of public climate attention at month t on downside risk at month t+1 under controlling high-degree fixed effects (Panel A), specific subsamples (Panel B), and alternative model specifications (Panel B), respectively. The dependent variables are corporate value at risk at bottom 5th percentile (*VaR*) and the second-order lower partial moment (*LPM*). The main independent variable is climate attention (*Atten*), which is constructed based on the Baidu search index of 45 climate related keywords (see the detail of construction in Section 2.1). The sample is from January 2011 to December 2020. Standard errors for coefficients are clustered by firm and reported in parentheses. ***, **, and * represent statistical significance at 1, 5, 10% levels, respectively. Definitions for each variable can be found in Appendix A.

on more social responsibilities and play key roles in solving climate problems when they are aware of climate change. Therefore, we expect the positive relationship between climate attention and downside risk to be more prominent for SOEs.

Table 8 shows the regression results of SOEs and non-SOEs with downside risk proxied by *VaR* and *LPM*. Columns (1) and (2) show that the coefficient of public attention is significantly positive for both SOEs and non-SOEs when *VaR* is used to proxy downside risks. However, the test of coefficient difference shows that SOEs are more prominently and significantly affected by climate attention than non-SOEs. In columns (3) and (4), the result also holds when *LPM* is used to proxy downside risks. Overall, ownership type can affect the relationship between climate attention and future downside risk at the firm-level. Our findings substantiate the view that SOEs are less likely to respond to this variation of attention and are less likely to handle climate risks because of their special operation purpose and low efficiency, leading to higher future downside risk.

4.5 | Additional tests

4.5.1 | Effects of ESG performance

This section examines whether firms' sustainable performance (specifically, ESG performance) is involved in corporate risk management.[21] Firms' exposure to climate risk makes investors more concerned about corporate sustainability or environmental and social responsibility (Matos, 2020). ESG ratings provide a comprehensive assessment of firms' abilities to deal with long-term risks, such as climate risks. Investors may consider that firms with better ESG performance can more easily adapt to climate change and address climate risks when public attention arises, leading to decreased firm downside risk. Recent studies also document that investors demand ESG participation as an effective risk

[21] Some of the authors cited in this paper use CSR (corporate social responsibility) instead of ESG. Following Sautner and Starks (2021), we use ESG throughout this paper rather than alternating between ESG and CSR.

TABLE 7 High- versus low-emission firms

	VaR_{t+1}		LPM_{t+1}	
	High-emission	**Low-emission**	**High-emission**	**Low-emission**
	(1)	**(2)**	**(3)**	**(4)**
$Atten_t$	1.588***	1.318***	0.274***	0.205***
	(0.061)	(0.031)	(0.022)	(0.011)
MTB_t	0.050***	0.045***	0.017***	0.015***
	(0.006)	(0.003)	(0.002)	(0.001)
$Size_t$	−0.014	−0.023*	−0.029***	−0.031***
	(0.026)	(0.012)	(0.009)	(0.004)
$Freefloat_t$	−0.230***	−0.394***	−0.098***	−0.144***
	(0.068)	(0.033)	(0.026)	(0.012)
$Leverage_t$	−0.308***	−0.277***	−0.117***	−0.119***
	(0.092)	(0.046)	(0.036)	(0.017)
ROA_t	−0.138	−2.524***	0.112	−0.898***
	(0.566)	(0.251)	(0.214)	(0.096)
$Invest_t$	−1.247***	−0.432**	−0.371***	−0.061
	(0.372)	(0.200)	(0.136)	(0.076)
$Profit_t$	−0.229*	−0.128***	−0.086*	−0.029
	(0.136)	(0.049)	(0.051)	(0.018)
$Dividend_t$	−0.167***	−0.216***	−0.059***	−0.078***
	(0.015)	(0.007)	(0.005)	(0.003)
Age_t	−0.021***	−0.016***	−0.007***	−0.006***
	(0.003)	(0.001)	(0.001)	(0.001)
$Constant_t$	4.843***	5.188***	2.226***	2.347***
	(0.381)	(0.177)	(0.138)	(0.064)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	50,116	232,750	50,116	232,750
Adjusted R^2	0.196	0.190	0.183	0.174
	chi^2=7.79***		chi^2= 3.47*	

Note: This table reports the results of regression of public climate attention at month t on downside risk at month t+1 in terms of different carbon emissions. Columns (1) and (3) present results for high emission specifications. Columns (2) and (4) present results for low-emission specifications. The dependent variables are corporate value at risk at bottom 5th percentile (VaR) and the second-order lower partial moment (LPM). The main independent variable is climate attention (Atten), which is constructed based on the Baidu search index of 45 climate related keywords (see the detail of construction in 2.1 part). The sample is from January 2011 to December 2020. Standard errors for coefficients are clustered by firm and reported in parentheses. ***, **, and * represent statistical significance at 1%, 5%, 10% levels, respectively. Definitions for each variable can be found in Appendix 1.

hedge instrument to reduce corporate systemic or downside risks (Albuquerque et al., 2019; Cornell, 2021). Moreover, firms with better ESG performance are less vulnerable to firm-specific negative events (Diemont et al., 2016; Krüger, 2015), resulting in a reduction of downside risk. Therefore, the impact of climate attention on downside risk may be mitigated by excellent ESG performance.

We use three variables to capture firms' ESG performance. First, *HZ_ESG_A* is a dummy variable that is equal to one if a firm's Huazheng ESG rating is equal to or above the A level. The second variable to capture sustainable performance is *HX_CSR*, which is a dummy variable equal to one when a firm's social responsibility score is higher than the median value of the same industry in the same year. The third one is the variable *Bloomberg_ESG*, a continuous variable, representing the Bloomberg ESG scores in a given year.

Table 9 reports the regression results for the analyses on ESG performance. We augment the baseline model by interacting climate attention with the three ESG performance variables. Columns (1), (3) and (5) show the results of using *VaR* to proxy firm downside risk. Notably, the positive association between climate attention and downside risk remains highly significant at the 1% level. More importantly, coefficients of interaction terms in three columns are negative and significant at the 1% level, indicating that excellent ESG performance can alleviate the risk-increase effect of climate attention on downside risks. We can find similar conclusions in the regression results when using *LPM* as the downside risk proxy variable. Taken together, we demonstrate that excellent ESG performance plays a mitigating role in the relationship between climate attention and downside risk.

4.5.2 | Effects of extreme climate disasters

Since human attention is limited (Kahneman, 1973), people are more inclined to focus on personal experiences and extreme events that can grab attention. For example, when people think they have experienced global warming (e.g., extremely high temperatures), they are more inclined to believe in climate change (Myers et al., 2013; Zaval et al., 2014). Therefore, extreme climate disasters will serve as a wake-up call for investors to focus on climate change and have a substantial impact on their risk perception, which has been confirmed by many studies.[22] Given that public attention will exacerbate downside risks, we believe the effect may be more prominent when extreme climate disasters occur because the soaring public attention will accelerate investors' consideration of climate risks in portfolios and firms' exposure to climate risks.

Specifically, in this paper, we consider major climate disasters that cause the most economic damage following Fich and Xu (2021). Major disasters are usually characterized by, geographically, widespread in their direct impact, more serious economic losses, and greater social impact. Additionally, such disasters can be more concerned and widely reported by the media and known to the public. Considering we capture the climate attention at the aggregate level, only such disasters can better draw public attention and have a material impact on public risk perceptions of climate change.

We construct a dummy variable *Disaster*, which equals one if a major climate disaster occurred during the month *t*, and divides the sample into two groups. Panel A of Table 10 reports the tests for differences in means analysis of our main variables. Major disasters are associated with higher

[22] For more information about this view, see Bergquist et al. (2019); Dai et al. (2015); Wachinger et al. (2013).

TABLE 8 SOEs versus non-SOEs

	VaR_{t+1}		LPM_{t+1}	
	SOE	**Non-SOE**	**SOE**	**Non-SOE**
	(1)	**(2)**	**(3)**	**(4)**
$Atten_t$	1.861***	1.052***	0.389***	0.108***
	(0.038)	(0.038)	(0.014)	(0.014)
MTB_t	0.052***	0.042***	0.018***	0.014***
	(0.005)	(0.003)	(0.002)	(0.001)
$Size_t$	−0.056***	0.032**	−0.043***	−0.013**
	(0.015)	(0.015)	(0.006)	(0.005)
$Freefloat_t$	−0.226***	−0.386***	−0.088***	−0.141***
	(0.049)	(0.038)	(0.018)	(0.014)
$Leverage_t$	−0.195***	−0.333***	−0.089***	−0.137***
	(0.064)	(0.054)	(0.024)	(0.020)
ROA_t	−0.726*	−3.011***	−0.228	−1.039***
	(0.401)	(0.277)	(0.154)	(0.106)
$Invest_t$	−1.079***	−0.405*	−0.339***	−0.043
	(0.321)	(0.213)	(0.122)	(0.080)
$Profit_t$	−0.183**	−0.156***	−0.054*	−0.041*
	(0.079)	(0.056)	(0.029)	(0.021)
$Dividend_t$	−0.207***	−0.202***	−0.077***	−0.072***
	(0.011)	(0.008)	(0.004)	(0.003)
Age_t	−0.008***	−0.021***	−0.003***	−0.008***
	(0.002)	(0.002)	(0.001)	(0.001)
$Constant_t$	5.316***	4.418***	2.395***	2.088***
	(0.240)	(0.213)	(0.089)	(0.077)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	107,970	174,896	107,970	174,896
Adjusted R^2	0.216	0.173	0.202	0.156
Difference-test for the coefficients of $Atten_t$	$\chi^2 = 112.89$***		$\chi^2 = 94.89$***	

Note: This table reports the results of regression of public climate attention at month t on downside risk at month t+1 in terms of different ownership types. Columns (1) and (3) present results for SOEs specifications. Columns (2) and (4) present results for non-SOEs specifications. The dependent variables are value at risk at bottom 5th percentile (VaR) and the second-order lower partial moment (LPM). The main independent variable is climate attention (Atten), which is constructed based on the Baidu search index of 45 climate related keywords (see the detail of construction in 2.1 part). The sample is from January 2011 to December 2020. Standard errors for coefficients are clustered by firm and reported in parentheses. ***, **, and * represent statistical significance at 1%, 5%, 10% levels, respectively. Definitions for each variable can be found in Appendix 1.

downside risk for firms and higher public climate attention in month t. More specifically, the mean *Atten* is 0.127 with no major disasters and 0.143 for public experienced major disasters. The difference is statistically significant at the 1% level, implying major disasters heighten public concern about climate change. However, the mean *VaR* and *LPM* in the month t+1 decrease following the occurrence of a major disaster. The results show that the major disaster may only increase downside risk in the month immediately it occurred, but not after.

We re-estimate our baseline model with the interaction term *Disaster*×*Atten*.[23] Columns (1) and (2) of Panel B in Table 10 report the regression results. the coefficient of *Atten* remains positive and significant when downside risk is measured by *VaR*, which is in line with our previous conclusions. Moreover, both of the interaction variables of *Disaster*×*Atten* carry a positive coefficient, significant at the 1% level. The results demonstrate that changes in climate attention brought by major climate disasters can explain changes in firm-level downside risks.

Next, a potential concern is that climate disasters affect downside risk by increasing the physical-level negative impact on firms instead of public attention. To ensure that the increasing downside risk is attributable to changes in climate attention, that is, the update of climate belief, we manually match the major stricken areas of the climate disasters with the headquarters of listed firms. We exclude firm-month

[23] To avoid strong collinearity effects, we do not control the *Disaster* in the regression model separately. But we also re-estimate the baseline model with including *Disaster* and these unreported coefficients remain significantly positive.

TABLE 9 The effect of ESG performance

	VaR_{t+1}	LPM_{t+1}	VaR_{t+1}	LPM_{t+1}	VaR_{t+1}	LPM_{t+1}
	(1)	(2)	(3)	(4)	(5)	(6)
$Atten_t$	1.423***	0.234***	2.955***	0.791***	2.232***	0.473***
	(0.033)	(0.012)	(0.035)	(0.013)	(0.116)	(0.043)
$HZ\_ESG\_A_t$	−0.118***	−0.040***				
	(0.015)	(0.006)				
$HZ\_ESG\_A\times Atten_t$	−0.145***	−0.043***				
	(0.042)	(0.016)				
HX_CSR_t			−0.010	−0.002		
			(0.015)	(0.006)		
$HX\_CSR\times Atten_t$			−0.195***	−0.064***		
			(0.045)	(0.017)		
$Bloomberg\_ESG_t$					−0.005**	−0.002**
					(0.002)	(0.001)
$Bloomberg\_ESG\times Atten_t$					−0.026***	−0.008***
					(0.005)	(0.002)
MTB_t	0.045***	0.015***	0.045***	0.014***	0.065***	0.024***
	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)	(0.002)
$Size_t$	−0.008	−0.027***	−0.025**	−0.035***	−0.050***	−0.038***
	(0.011)	(0.004)	(0.011)	(0.004)	(0.016)	(0.006)
$Freefloat_t$	−0.348***	−0.130***	−0.347***	−0.133***	−0.180***	−0.062***
	(0.030)	(0.011)	(0.030)	(0.012)	(0.048)	(0.018)
$Leverage_t$	−0.292***	−0.122***	−0.342***	−0.140***	−0.050	−0.039
	(0.041)	(0.015)	(0.042)	(0.016)	(0.071)	(0.027)
ROA_t	−2.106***	−0.720***	−2.691***	−1.033***	−2.410***	−0.958***
	(0.232)	(0.088)	(0.245)	(0.093)	(0.362)	(0.141)
$Invest_t$	−0.563***	−0.115*	−1.544***	−0.528***	−0.235	0.022
	(0.177)	(0.067)	(0.181)	(0.068)	(0.308)	(0.117)
$Profit_t$	−0.143***	−0.037**	−0.096*	−0.026	−0.203**	−0.053*
	(0.047)	(0.017)	(0.051)	(0.019)	(0.087)	(0.032)
$Dividend_t$	−0.201***	−0.073***	−0.217***	−0.078***	−0.164***	−0.059***
	(0.006)	(0.002)	(0.008)	(0.003)	(0.009)	(0.003)
Age_t	−0.016***	−0.006***	−0.017***	−0.006***	−0.009***	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
$Constant_t$	4.939***	2.267***	5.275***	2.427***	5.150***	2.258***
	(0.162)	(0.059)	(0.164)	(0.060)	(0.248)	(0.092)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	282,866	282,866	248,478	248,478	107,825	107,825
Adjusted R^2	0.191	0.175	0.230	0.214	0.232	0.217

Note: This table reports whether excellent ESG performance alleviates the adverse effect of rising public climate attention at month t on downside risk at month t+1. The dependent variables are value at risk at bottom 5th percentile (*VaR*) and the second-order lower partial moment (*LPM*). We use three variables to capture ESG performance: Huazheng ESG rating which is equal to or higher above A level (*HZ_ESG_A*), Hexun CSR which is equal to one when a firm's social responsibility score is higher than the median value of the same industry in the same year (*HX_CSR*), and Blommberg ESG scores (*Bloomberg_ESG*). Public climate attention (*Atten*) is constructed based on the Baidu search index of 45 climate related keywords (see the detail of construction in 2.1 part). We interact the variable *Atten* with proxy variables of ESG performance. The sample is from January 2011 to December 2020. Standard errors for coefficients are clustered by firm and reported in parentheses. ***, **, and * represent statistical significance at 1%, 5%, 10% levels, respectively. Definitions for each variable can be found in Appendix 1.

TABLE 10 The effect of extreme climate disasters

Panel A: Differences in mean analysis of main variables

	$Disaster_t$=0 (1)		**$Disaster_t$=1 (2)**		**Difference (1)-(2)**	
	Mean	**N**	**Mean**	**N**	**MeanDiff**	***P*-value**
$Atten_t$	0.127	161,881	0.143	42,289	−0.016	0.000***
VaR_t	4.283	161,880	4.464	42,289	−0.181	0.000***
LPM_t	1.660	161,682	1.745	42,241	−0.085	0.000***
VaR_{t+1}	4.372	161,881	3.936	42,289	0.436	0.000***
LPM_{t+1}	1.653	161,881	1.610	42,289	0.043	0.000***

Panel B: The effect of climate disasters

	VaR_{t+1}	**LPM_{t+1}**	**VaR_{t+1}**	**LPM_{t+1}**	**VaR_{t+1}**	**LPM_{t+1}**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
$Atten_t$	0.914***	−0.051***	0.861***	−0.070***	−4.660***	−1.701***
	(0.032)	(0.012)	(0.033)	(0.012)	(0.045)	(0.019)
$Atten \times Disaster_t$	0.812***	0.877***	0.762***	0.847***		
	(0.050)	(0.018)	(0.053)	(0.020)		
$Damage_t$					−0.137***	−0.045***
					(0.001)	(0.000)
$Atten \times Damage_t$					0.642***	0.206***
					(0.005)	(0.002)
MTB_t	0.050***	0.017***	0.052***	0.017***	0.052***	0.017***
	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
$Size_t$	−0.011	−0.028***	−0.003	−0.026***	−0.008	−0.027***
	(0.012)	(0.004)	(0.012)	(0.004)	(0.012)	(0.004)
$Freefloat_t$	−0.358***	−0.133***	−0.359***	−0.134***	−0.380***	−0.143***
	(0.037)	(0.014)	(0.037)	(0.014)	(0.036)	(0.014)
$Leverage_t$	−0.278***	−0.111***	−0.294***	−0.116***	−0.306***	−0.123***
	(0.047)	(0.018)	(0.047)	(0.018)	(0.047)	(0.017)
ROA_t	−3.155***	−0.938***	−3.460***	−1.026***	−4.746***	−1.612***
	(0.281)	(0.108)	(0.282)	(0.108)	(0.288)	(0.111)
$Invest_t$	−0.722***	−0.022	−0.867***	−0.064	−1.989***	−0.531***
	(0.234)	(0.088)	(0.235)	(0.089)	(0.238)	(0.090)
$Profit_t$	−0.105**	−0.039**	−0.080	−0.031	0.055	0.028
	(0.053)	(0.020)	(0.054)	(0.020)	(0.053)	(0.020)
$Dividend_t$	−0.206***	−0.075***	−0.206***	−0.076***	−0.194***	−0.071***
	(0.007)	(0.003)	(0.007)	(0.003)	(0.007)	(0.003)
Age_t	−0.017***	−0.006***	−0.017***	−0.006***	−0.018***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$Constant_t$	4.963***	2.314***	4.871***	2.283***	6.354***	2.782***
	(0.175)	(0.064)	(0.176)	(0.064)	(0.176)	(0.064)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204,170	204,170	200,303	200,303	204,170	204,170
Adjusted R^2	0.215	0.197	0.209	0.191	0.256	0.223

Note: Panel A reports the differences in means analysis of firm-level downside risk and public climate attention, respectively, for the sample of major disasters that happened versus no major disasters happened. Panel B reports whether major climate disasters reinforce the adverse effect of rising public climate attention at month t on downside risk at month t+1. The dependent variables are value at risk at bottom 5th percentile (VaR) and the second-order lower partial moment (LPM). The public climate attention (Atten) is constructed based on the Baidu search index of 45 climate related keywords (see the detail of construction in 2.1 part). Disaster takes a value of one if a major climate disaster occurred during the month t and zero if not. Damage measures the total economic losses brought by climate disasters in a given month. We interact the variable Atten with disaster proxy variables. The sample is from January 2014 to December 2020. Standard errors for coefficients are clustered by firm and reported in parentheses. ***, **, and * represent statistical significance at 1%, 5%, 10% levels, respectively. Definitions for each variable can be found in Appendix 1.

observations suffering major climate disasters. Columns (3) and (4) of Panel B show the regression results after elimination. The interaction coefficient estimates remain positive and significant at the 1% level. This indicates that our findings are a result of enhancing climate beliefs.

Lastly, we use the total economic loss that occurred in month t, *Damage*, to measure climate disasters. We re-estimate our baseline model with the interaction variable of *Atten*×*Damage*. Columns (5) and (6) of Panel B represent the results. As expected, the estimates for the interaction term load positively and significantly.

Generally, we find that the occurrence of climate disasters can amplify the positive impact of climate attention on firm-level downside risks, indicating that public beliefs are updated with major climate events.

5 | CONCLUSIONS AND DISCUSSION

In this study, we explore whether collective climate attention, captured by the Baidu search volume index, affects downside risk. We find that climate attention has a significant and positive effect on downside risk at both market-level and firm-level. Moreover, the risk-increase effect of climate attention is stronger in the SOEs and high-carbon emission industries. Further analysis shows that firms with excellent sustainable performance can alleviate the adverse effects of rising climate concerns. While human attention remains limited, investors react to major climate events and update their beliefs on climate change. We document evidence that climate attention will soar when extreme climate disasters occur, exacerbating its effect on downside risks.

While our work suggests that public climate attention harms corporate downside risk, there remain a few limitations and open questions that need to be addressed. Most significantly, although we explore some potential mechanisms that drive climate concerns to associate higher downside risks, for example, ESG performance and major climate disasters, there may be other mechanisms unexplored. Future work could probe this area by looking over other potential mechanisms. In addition, the limitations of the attention measurement should be mentioned. While capturing changes in both public awareness and perception effectively, internet search volumes only act as ring bells to determine the importance of the issue instead of the rationale behind why the issue is important (Lineman et al., 2015). What motivates the public to search for each term is unknown. It would be insightful to account for these important facts when we use the search tool. The last potentially serious limitation is that climate attention measured by the Baidu search trend only goes back to January 2011. Many policies related to climate change and corporate mitigation action are usually undertaken over the years instead of months, and climate attention varies greatly not only within but across generations. Therefore, ten years of data limits our capability to discuss and draw conclusions about the association between long-term changes in climate attention and corporate risk management.

Despite these limitations and challenges, our findings confirm the significance of collective climate beliefs in firm risk management and provide a reference for the investor's decision making in emerging markets. For corporate managers, they could be motivated by the results to take action toward preparing themselves for the potential damages of public climate concern. For investors, given that they are aware of climate risks to their portfolios, they should prioritize firms with better sustainable performance. In such a way, investors are more likely to avoid the losses brought by climate risks in their investment. All in all, understanding the impact of climate attention on economic outcomes is an interesting and continued endeavor, we hope that our findings motivate other researchers to explore this important topic.

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APPENDIX A

TABLE A1 Variable definitions

Variables	Descriptions
Downside risk variables	
VaR_{t+1}	Variable of value at risk, calculated as the bottom 5th percentile of the daily returns in month t+1, which is usually corresponds to the worst return. Then we take the absolute value to ensure VaR is positive.
LPM_{t+1}	Variable of the second-order lower partial moment, calculated as the square root of the semi-variance below 0%. For firm i in month $t+1$, this measure is defined as$LPM = \sqrt{\frac{1}{N_1-1}\sum_{i=1}^{N_1}(r_{n,i}-\bar{r}_{n,i})^2}$ where N_1 is the number of observations of negative returns for firm i in month t+1, $r_{n,i}$ is the negative return on firm i and $\bar{r}_{n,i}$ is the mean value of $r_{n,i}$.
$VaR5_{t+1}$ ($VaR1_{t+1}$)	Variables of value at risk, calculated as the 5th (1st) percentile of the daily returns during the period from the past one year to the end of month t+1 following Atilgan et al. (2020). The values calculated for less than 200 non-missing return observations in the past year are excluded. We take the absolute values of VaR.
$ES5_{t+1}$ ($ES1_{t+1}$)	Variables of expected shortfall, calculated as the average losses of that are less than or equal to the 5th (1st) percentile of the daily returns during the period from the past one year to the end of month t+1 following Atilgan et al. (2020). The values calculated for less than 200 non-missing return observations in the past year are excluded. We take the absolute values of ES.
Public climate attention variables	
$Atten_t$	A proxy variable for public climate attention. After manually collecting the Baidu daily SVI of the 45 keywords from five different categories related to climate change, we calculate the monthly average value of each keyword. Then, we apply factor analysis to extract common factors and construct the climate attention monthly by calculating the comprehensive factor scores. We also conduct a seasonal adjustment to climate attention. For more details of construction, see Section 2.1.
Market-level control variables	
VIX_t	CBOE China ETF Volatility Index.
EPU_t	Calculated as the changes in newspaper-based economic policy uncertainty of China.
BC_t	Calculated as the changes in business confidence index.
MP_t	Calculated as the changes in macro prosperity coincident index.
Firm-level control variables	
MTB_t	Calculated as the market value of equity to the book value of equity.
$Size_t$	The natural logarithm of total assets in the quarter.
$Freefloat_t$	Calculated as the number of shares available in the free float scaled by number of shares issued.
$Leverage_t$	Calculated as total debt scaled by common equity
ROA_t	Calculated as net profit after tax scaled by total assets
$Profit_t$	Calculated as operating income scaled by total sales
$Invest_t$	Calculated as capital expenditures scaled by assets.
$Dividend_t$	Calculated as dividends per share scaled by the share price.
Age_t	Calculated as the difference between listing date and observation month, measured by year.
High carbon emission industries	
$High\text{-}emission_t$	Dummy variable which equals one if a firm belongs to carbon-intensive industries, implementing carbon emissions trading, and zero otherwise.
State-owned-enterprises	
SOE_t	Dummy variable which equals one if a firm is a State-owned enterprise (SOE) and zero otherwise.
Sustainable performance	
$HZ\_ESG\_A_t$	Dummy variable which equals one if a firm's ESG rating of HuaZheng is A or above A, and zero otherwise.
HX_CSR_t	Dummy variable which equals one if a corporate Hexun social responsibility score is higher than the median scores in the same industry and year and zero otherwise.

(Continues)

TABLE A1 (Continued)

Variables	Descriptions
Bloomberg_ESG	The Bloomberg ESG scores for a firm in a given year.
Other variables of interest	
$InsHold_t$	The proportion of shares held by institutional investors.
$Disaster_t$	Dummy variable which equals one if a major climate-related natural disaster occurred during the month t and zero otherwise.
$Damage_t$	The natural logarithm of total economic losses brought by climate disasters in a given month with no limit to the major disasters.

APPENDIX B

Searching topics about climate change

The analysis in Section 2.1.1 shows that public climate attention can be characterized by five different categories related to the definition and impact of climate change. They are broad cognitive level, physical attention, regulatory attention, opportunity attention, and climate frontier conference, specifically. Below we report the resulting keywords, in Chinese, in decreasing order of importance (as measured by average monthly search volume index). Then, we report the translated words in parentheses.

(i) Broad cognitive level category: 全球变暖, 气候, 气候类型, 气候变化, 气候变暖, 气候带, 气候异常 (in English: global warming, climate, climate type, climate change, climate warming, climate zone, climatic anomaly).
(ii) Physical attention category: 二氧化碳, 厄尔尼诺, 热带雨林, 环境污染,温室效应, 极端天气, 大气污染,温室气体, 臭氧层, 海平面上升, 能源危机, 土地沙漠化,冰山融化 (in English: carbon dioxide, El Niño, rainforest, environmental pollution, greenhouse effect, extreme weather, air pollution, greenhouse gas, ozone layer, sea-level rise, energy crisis, land desertification, ice cap melting).
(iii) Regulatory attention category: 节能减排, 低碳经济, 碳交易,碳排放, 能源管理, 碳足迹, 碳关税, 减少碳排放 (in English: carbon reduction, low-carbon economy, carbon trade, carbon emission, energy regulatory, carbon footprint, carbon taxes, reduce emission).
(iv) Opportunity attention category: 太阳能, 光伏, 新能源, 核能, 清洁能源,可再生能源, 地热能, 风能, 绿色金融,氢能, 绿色能源 (in English: solar energy, photovoltaic, new energy, nuclear power, clean energy, renewable energy, geothermal energy, wind power, green finance, hydrogen energy, green energy).
(v) Climate commission category: *巴黎协定,哥本哈根气候大会, 气候大会, 京都协议书, 联合国气候大会, 气候变化研究进展* (in English: the Paris Agreement, Copenhagen Climate Change Conference, climate conference, the Kyoto protocol, United Nations climate conference, progress in climate research).

APPENDIX C

TABLE C1 Measure public climate attention under a detrending method

	VaR_{t+1} (1)	VaR_{t+1} (2)	LPM_{t+1} (3)	LPM_{t+1} (4)
$Atten\_Detrend_t$	1.084***	1.065***	0.144***	0.140***
	(0.025)	(0.025)	(0.009)	(0.009)
MTB_t		0.049***		0.016***
		(0.003)		(0.001)
$Size_t$		−0.005		−0.026***
		(0.011)		(0.004)
$Freefloat_t$		−0.381***		−0.143***
		(0.031)		(0.012)
$Leverage_t$		−0.330***		−0.132***
		(0.043)		(0.016)
ROA_t		−2.645***		−0.776***
		(0.244)		(0.093)
$Invest_t$		−0.952***		−0.158**
		(0.188)		(0.071)
$Profit_t$		−0.120**		−0.042**
		(0.048)		(0.018)
$Dividend_t$		−0.205***		−0.074***
		(0.007)		(0.002)
Age_t		−0.018***		−0.007***
		(0.001)		(0.001)
$Constant_t$	4.140***	4.932***	1.594***	2.265***
	(0.010)	(0.164)	(0.004)	(0.060)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	263,276	263,276	263,276	263,276
Adjusted R^2	0.167	0.196	0.150	0.180

Note: This table reports the additional test results of the regression of public climate attention at month t on downside risk at month *t*+1. The dependent variable in columns (1) and (2) is value at risk at bottom 5th percentile (*VaR*) at firm-level. In columns (3) and (4), the dependent variable is the second-order lower partial moment (*LPM*) at firm-level. The main independent variable is climate attention (*Atten*), which is detrended by subtracting the average factor score during the previous 12 months. The sample is from January 2012 to December 2020. Standard errors for coefficients are clustered by firm and reported in parentheses. ***, **, and * represent statistical significance at 1, 5, 10% levels, respectively. Definitions for each variable can be found in Appendix A.

APPENDIX D

TABLE D1 Sample of the major climate disasters

No.	Events	Announcement date	Damages(Billion CNY)	Damages(CPI adjusted)	Fatalities
1	Drought	8/14/2014	40.59	45.20	0
2	Typhoon	7/13/2015	8.56	9.23	0
3	Drought	7/22/2015	11.48	12.38	0
4	Typhoon	8/10/2015	8.00	8.63	21
5	Typhoon	8/11/2015	13.77	14.85	26
6	Typhoon	8/12/2015	18.19	19.62	26
7	Typhoon	10/8/2015	28.99	31.27	19
8	Hypothermia	1/25/2016	41.01	43.69	6
9	Storm	6/22/2016	9.67	10.30	42
10	Storm	7/4/2016	20.44	21.77	93
11	Flood	7/21/2016	10.71	11.41	20
12	Storm	7/22/2016	11.49	12.24	57
13	Flood	7/22/2016	11.14	11.87	23
14	Drought	8/10/2016	8.39	8.94	0
15	Drought	8/17/2016	7.22	7.69	0
16	Typhoon	9/19/2016	15.49	16.50	29
17	Storm	6/26/2017	9.48	9.88	28
18	Storm	7/3/2017	18.88	19.69	33
19	Storm	7/4/2017	25.27	26.35	40
20	Storm	7/20/2017	22.25	23.21	19
21	Typhoon	8/25/2017	12.18	12.71	11
22	Hail	4/9/2018	8.17	8.32	0
23	Flood	11/19/2018	7.43	7.56	0
24	Storm	6/11/2019	7.14	7.14	32
25	Storm	6/25/2019	6.47	6.47	14
26	Flood	7/9/2019	7.11	7.11	10
27	Flood	7/10/2019	11.76	11.76	15
28	Storm	7/16/2019	6.81	6.81	6
29	Typhoon	8/12/2019	23.46	23.46	42
30	Typhoon	8/15/2019	40.90	40.90	53

Note: This table reports information about the major climate disasters according to direct economic damage (adjusted for inflation) that occurred in China from January 2014 to December 2020. *Damages* is the estimated value of direct economic damage expressed in billions of CNY for each climate disaster. *Damages (CPI adjusted)* is the estimated value of direct economic damage expressed in billions of CNY adjusted for the Consumer Price Index as of 2019. We obtain data from CSMAR, which collects disaster data from news reported by the National Disaster Reduction Center of China (NDRCC).