China Journal of Accounting Research 18 (2025) 100446

Contents lists available at ScienceDirect

China Journal of Accounting Research

journal homepage: www.elsevier.com/locate/cjar

Climate risk and adaptive green innovation: evidence from China

Xudong Tang [a], Lin Wang [a,b], Lulu Pan [c,*]

[a] School of Business Administration, South China University of Technology, Research Area: Corporate Finance, Corporate Governance, Capital Markets, China
[b] School of Management, Xiamen University. Research Interests: Corporate Finance, Capital Markets, China
[c] Faculty of Environment and Construction, Hong Kong Polytechnic University, Research Area: Environmental Economics, Hong Kong

ARTICLE INFO

Article history:
Received 6 November 2024
Accepted 15 September 2025
Available online 3 October 2025

Keywords:
Climate risk
Green innovation
Strategic adaptation

ABSTRACT

Firms' adaptation to climate risk is crucial for economic resilience. This paper links 2724 Chinese meteorological stations with A-share listed firms from 2006 to 2020 by geographic proximity. We construct a comprehensive climate risk measure via the entropy method and find that climate risk can promote green invention patent applications at the firm level. Mechanistically, climate risk drives green innovation by strengthening external government environmental regulations and internal corporate environmental responsibility. The effect is stronger in non-polluting industries and when firms receive more attention from social media. This study enhances understanding of firms' positive adaptation to climate risk and offers new insight into green innovation drivers.

1. Introduction

Climate change is posing unprecedented challenges to the global workforce and economic systems (He et al., 2022). Over 70 % of the global workforce—approximately 2.4 billion people—faces significant climate risk. Research extensively explores the wide-ranging socio-economic costs of climate change, including ecological degradation (Ciais et al., 2005), health impairments (Chavaillaz et al., 2019) and agricultural yield fluctuations (Hogan & Schlenker, 2024). However, the strategic adaptation behaviors of firms in response to these climate challenges remain largely unexplored.

Green innovation, a crucial strategic adaptive behavior enabling firms to deal with climate risk (Liu et al., 2024), is both defensive (mitigating risk) and proactive (creating opportunities), enabling firms to maintain

* Corresponding author at: Block Z, The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong.
E-mail address: lulu1997.pan@connect.polyu.hk (L. Pan).

https://doi.org/10.1016/j.cjar.2025.100446
1755-3091/

competitiveness and relevance in the face of evolving environmental and market conditions. Many enterprises are stepping up their efforts to develop green and innovative technologies in areas such as exhaust gas management, energy conservation and the low carbon economy (as shown in Appendix I), helping to ameliorate climate change related problems such as global warming and environmental degradation. These practices also provoke extensive academic reflection on whether climate risk induces firms to adopt such strategic adaptive behaviors. This is theoretically important. If firms lack the capacity to deal with climate risk and have limited adaptive measures, such risk could exert cumulative negative effects on the stability of economic systems (Sun et al., 2024). Conversely, if firms swiftly implement long-term strategic adaptation measures to address climate risk, they can effectively mitigate direct economic losses and contribute to the broader transformation of the economic system to achieve greater climate resilience and sustainability.

However, studies report inconsistent conclusions regarding the relationship between climate risk and corporate green innovation. On the one hand, under climate change, attention and supervision from governments, society and the public can push enterprises to invest more in green innovation (Alam et al., 2022; Hou et al., 2024; Wang et al., 2024). On the other hand, climate risk can also majorly damage the economy, distort innovation resource allocation and reduce firms' green innovation capacity (Wen et al., 2023; Deng et al., 2024; Liu et al., 2024). Previous studies mainly match climate risk to firms using national or regional data, which may not capture the climate risk to which firms are directly exposed. Given that green innovation is an important way to promote sustainable development, it is necessary to scrutinize the impact of climate risk on corporate green innovation using more specific firm-level indicators.

In this study, we first measure firm-level climate risk based on geographic matching between listed companies and meteorological stations. Specifically, we match each listed company with the nearest meteorological station based on geographic proximity, enabling us to obtain daily weather information for the company's office locations. Using the entropy method, we construct a comprehensive measure of climate risk. Next, we empirically examine the impact of climate risk on corporate green innovation with data drawn from A-share listed companies from 2006 to 2020. The results indicate that local climate risk significantly promotes corporate green innovation. Mechanism tests show that climate risk strengthens both external government environmental regulations and internal corporate environmental responsibility, leading to more green innovation. Furthermore, the positive effect of climate risk is more pronounced when firms operate in non-polluting (vs. polluting) industries and receive greater attention from social media.

This study contributes to the literature in the following ways. First, we expand firm-level climate risk indicators. Most studies rely on macro-level data, such as provincial temperature anomalies or national vulnerability indices, which fail to precisely capture firm-specific exposure. Although some firm-level studies employ lexical analysis to measure climate risk perception (Tian et al., 2024), they do not quantify actual physical climate risk. Our study constructs a multidimensional climate risk measure at the firm level, which integrates temperature and precipitation sub-indicators and applies the entropy method to objectively weigh these dimensions. This approach overcomes the limitations of single-dimensional metrics (Wu, 2025) by simultaneously capturing risk frequency, intensity and long-term trends.

Second, the paper uses granular data to demonstrate that climate risk promotes corporate green innovation. Previous studies reach no unified conclusion on whether climate risk boosts or inhibits corporate green innovation. Moreover, most studies focus on national or regional indicators, and their portrayal of climate risk at the firm level is relatively coarse. This paper innovatively uses more granular data to match firms with their neighboring weather stations, thereby more appropriately measuring the climate risk to which a firm is exposed. This is achieved by constructing a comprehensive measure using the entropy method, providing a more realistic and nuanced understanding of the climate fluctuations to which firms are exposed. The results show that climate risk has a positive effect on corporate green innovation. This enriches research on the relationship between climate risk and corporate green innovation and provides a new data perspective for subsequent studies.

Lastly, this paper conducts heterogeneity analyses at the firm level (the degree of pollution) and the external stakeholder level (social media). Our findings reveal that climate risk exerts a nuanced and heterogeneous effect on green innovation. We find that the positive effect of climate risk is significantly more pronounced for non-polluting firms and firms that receive greater attention from social media. This contributes to a deeper understanding of the contingent effects of climate risk on corporate green innovation, highlighting that its impact is not uniform but depends on specific firm characteristics and external pressures.

Section 2 reviews the relevant literature and identifies the research gaps created by mixed findings. Section 3 develops the hypotheses, and Section 4 discusses the research design. Section 5 reports the empirical results. In Section 6, we conclude the study and provide policy implications.

2. Literature review

2.1. Climate risk and corporate behavior

Charpentier (2008) defines climate risk as the risk resulting from climate change, such as health risks posed by new diseases and economic impacts on industries such as agriculture and manufacturing. The literature broadly identifies the effects of climate risk on corporate operation and investment decisions.

First, while climate risk can increase firms' production and operational costs, it may also encourage companies to adopt more sustainable practices within their production processes to mitigate the environmental and other impacts of climate change. As Pankratz et al. (2023) demonstrate, an increase in extreme temperatures reduces firms' revenue. Similarly, Addoum et al. (2023) explore how the impacts of extreme temperatures vary across industries, causing harm to some while bringing benefits to others. Huang et al. (2018) indicate that the likelihood of suffering losses from meteorological disaster events is correlated with lower and more volatile earnings and cash flows. In harsher climate conditions, firms are more likely to hold more cash reserves to establish financial buffers, increasing their organizational resilience to climate threats. Additionally, Ilhan et al. (2023) find that institutional investors actively engage with firms to improve the transparency of their climate risk disclosure. Li et al. (2025) demonstrate that companies that are more influenced by Confucianism exhibit greater climate change awareness.

Second, regarding investment and financing, climate risk compels firms to enhance their risk management related to climate issues and to attach more importance to corporate social responsibility (CSR). Krueger et al. (2020) find that many market participants, including institutional investors, perceive climate risk as difficult to price and hedge, potentially due to its systemic characteristics, insufficient disclosures by portfolio companies and the challenges involved in finding appropriate hedging tools. The notion that incorporating climate risk into the investment process can improve investment returns and reduce portfolio risk is also supported. Furthermore, Ozkan et al. (2023) show that firms located in countries with higher climate risk tend to undertake more CSR activities. This may indicate that companies cope with climate risk by increasing their CSR initiatives, and that, in turn, higher levels of CSR significantly mitigate the negative influence of climate risk on firm performance.

2.2. Drivers of green innovation

Corporate green innovation has a dual nature: it is both a practical activity closely related to a firm's daily operations (Rennings, 2000) and a long-term strategic investment aimed at adapting to climate risk (Rodima-Taylor et al., 2012). A substantial body of literature addresses the factors influencing corporate green innovation investment, which fall into two main categories: external institutional and policy factors and internal corporate strategy, knowledge and governance factors.

The literature explores whether external environmental regulatory policies contribute to varying degrees of green innovation. Rennings (2000) argues that besides technology-push and market-pull factors, environmental regulatory frameworks serve as a driving force. This aligns with the Porter hypothesis, which emphasizes the importance of environmental regulations in stimulating green innovation (Porter & van der Linde, 1995). Gugler et al. (2024) further analyze whether policy instruments such as environmental regulation, taxes and research and development (R&D) subsidies play a role in increasing green innovation. In the context of China, research shows that environmental policies—such as the Total Emission Control Policy (Yan et al., 2024), the Environmental Protection Law (Huang et al., 2023), and environmental courts (Qi et al., 2023)—promote green innovation, although they exert varying effects on innovation quality. Another strand of the literature, such as Sun et al. (2024), demonstrates that ESG performance within the supply chain affects green innovation.

Internal factors within firms are vital in driving green innovation, and the literature explores these internal drivers from multiple perspectives, such as internal knowledge accumulation (Wang & Juo, 2021), the characteristics of top management (Quan et al., 2023), external relationships (Sun et al., 2024) and internal governance (Amore & Bennedsen, 2016).

2.3. Research on climate risk and green innovation: Mixed findings and gaps

2.3.1. Mixed findings

This section highlights the mixed findings of previous research regarding climate risk and its impact on green innovation. Accordingly, it identifies the research gaps that this paper seeks to address through a comprehensive measurement approach. Several studies explore the impact of climate risk on green innovation, yet their findings are often contradictory.

Some studies report that climate risk promotes green innovation. At the national level, Alam et al. (2022) focus on the impact of climate change on innovation in small and medium-sized enterprises (SMEs) in developing countries, noting that innovation investment can help SMEs to cope with climate shocks. Additionally, the sudden and destructive nature of extreme heat and precipitation at the city and county levels attracts widespread attention from governments, the public and society, thereby promoting corporate green innovation (Hou et al., 2024; Wang et al., 2024). Studies constructing climate risk indicators from a corporate perspective are relatively scarce. Tian et al. (2024) and Ren et al. (2024) conduct textual analyses of corporate annual reports and find that perceived climate risk increases green innovation investment by stimulating digital transformation.

In contrast, some studies report that climate risk inhibits green innovation. Geographic conditions vary markedly from country to country, and nations are affected differently by global climate change. Many scholars examine corporate green innovation through national climate vulnerability indices, consistently finding that firms are less able to innovate in countries with greater exposure to climate risk (Wen et al., 2023; Deng et al., 2024; Liu et al., 2024). Furthermore, numerous scholars find that extreme heat, abnormal temperatures and meteorological disaster events in cities or provinces significantly reduce corporate profitability, increase operating costs and crowd out green R&D investment (Hu et al., 2022; He et al., 2024; Li et al., 2024; Agostino et al., 2025; Wang et al., 2025).

2.3.2. Limitations of the literature

Despite the extensive insights provided by the literature, two limitations remain. First, regarding measurement, many studies rely on national or regional data to proxy for firm-level climate risk, such as provincial abnormal temperatures or national climate vulnerability indices. These data may not adequately capture firms' actual exposure to climate risk. While Tian et al. (2024) and Ren et al. (2024) focus on firms, they measure climate risk perception using a Word2Vec model based on lexical patterns, rather than capturing the actual climate risk encountered by firms. Second, the previous literature primarily employs single-dimensional indicators to assess physical climate risk, such as abnormal temperature (Li et al., 2024), extreme heat (Hou et al., 2024) or extreme precipitation (Wang et al., 2024). Wu (2025) aggregates extreme high temperatures, low temperatures and precipitation days, focusing solely on the frequency of extreme events while overlooking risk intensity, duration and long-term trends, and assuming that all events are equally weighted. Instead, we utilize a comprehensive system incorporating temperature and precipitation-related subindicators, employing the entropy method to better capture the multidimensional characteristics of climate risk.

3. Hypothesis development

Theoretically, climate risk may pose at least two types of negative external shocks to the survival and development of firms. First, extreme weather events cause production losses (Benincasa et al., 2024), hindering firms from maintaining a market share and becoming more competitive (Linnenluecke et al., 2011;

Pankratz et al., 2023). Second, external stakeholders, including governments, shareholders, creditors, employees and the media, may pressure firms to transform (Krueger et al., 2020; Ilhan et al., 2023).

However, climate risk can be a positive catalyst for green innovation, driven by the firm's adaptive capacity and strategic responses. The theory of firm behavior posits that a firm is a goal-oriented organizational system with strong adaptive capabilities. When confronted with external disturbances or shocks beyond its control, the firm can adjust its decisions according to certain rules to achieve desired performance (Cyert & March 2006). From the perspective of internal decision-making rules, climate risk influences the dimensions of goals that firms prioritize when adjusting their behaviors based on feedback on performance. The presence of climate risk requires firms to move beyond focusing solely on short-term profit indicators when formulating strategies (Kolk & Pinkse, 2004). Instead, they must incorporate climate factors into their decision-making frameworks, reassessing and adjusting the dimensions of their goals while considering the impact of these adjustments on their long-term performance. This section analyzes how climate risk affects companies' green innovation by discussing external pressures on and internal motivations for their decision-making processes.

First, climate risk may compel firms to emphasize environmental protection by increasing the stringency of government environmental regulations, thereby driving firms to invest more in green innovation. This external pressure forces companies to reassess their production processes and business models to comply with increasingly stringent environmental standards. To adhere to new regulations and mitigate potential compliance risk, firms may ramp up their investment in green innovation (Hu et al., 2022). Relying on outdated production technologies and adopting production methods that appear safe in the short term but are non-compliant with new regulations will fail to effectively offset the high costs incurred under stricter environmental regulations.

Second, climate risk may also enhance firms' environmental responsibility awareness, prompting them to increase their environmental investments, which in turn boosts green innovation output. By disrupting normal business operations and exposing firms to physical and financial vulnerabilities, climate risk often serves as a wake-up call for companies to reconsider their long-term sustainability strategies. Faced with increasingly severe and frequent climate-related events, firms are compelled to increase their environmental responsibility awareness, which reflects their subjective willingness to engage and proactive engagement in environmental protection (Gadenne et al., 2009). Firms begin to recognize proactive environmental protection as essential not only for regulatory compliance but also for long-term competitiveness and resilience (Garel & Petit-Romec, 2021). As climate risk stimulates firms' environmental responsibility awareness, they are more likely to proactively increase their R&D investment, reduce their emissions and accelerate their green transition.

Therefore, our hypotheses are as follows:

H1. All else being equal, climate risk can effectively promote corporate green innovation.

H1a. Climate risk increases the intensity of external government environmental regulations, leading to more green innovation.

H1b. Climate risk enhances a firm's internal environmental responsibility awareness, leading to more green innovation.

From another perspective, however, climate risk may not significantly catalyze corporate green innovation. First, many aspects of climate risk, such as extreme heat and rainstorms, are inherently uncontrollable. Even if a firm invests heavily in green innovation, it may still suffer significant losses due to physical risk in high-risk areas, and innovation efforts may be undermined. This can directly offset the incentives that climate risk might otherwise provide for green innovation. Second, when firms face climate risk, mitigation strategies other than green innovation, such as purchasing insurance (Chang et al., 2018), are available. Firms can transfer risk to insurance companies by paying premiums to reduce their own losses. Green innovation requires the long-term investment of large amounts of capital and human resources, and the transformation process is uncertain. In contrast, based on risk avoidance and cost–benefit considerations, firms are more likely to choose alternative strategies, such as insurance. Lastly, green innovation is characterized by high investment, a long cycle and high risk (Hutchison-Krupat & Chao, 2014), and the impact of climate risk is uncertain and lagged. Firms need to weigh the expected inputs and returns when making green innovation decisions. The firm may not increase its green innovation investment if climate risk does not have a significant impact on its current operations, or if the firm believes that it will be difficult to obtain adequate returns on such innovation investment in the short term. Moreover, both the perception of and the ability to cope with climate risk vary across industries and firms, which can further influence green innovation decisions.

Therefore, our alternative hypothesis is as follows:

H2. All else being equal, climate risk does not effectively promote corporate green innovation.

4. Research design

4.1. Sample selection and data sources

We employ data drawn from Chinese A-share listed companies from 2006 to 2020 as our initial sample. The data exclusion criteria are as follows: (1) special treatment (ST) and ST* firms; (2) financial firms; (3) samples with missing variable observations; (4) firms with leverage ratios greater than or equal to 1; and (5) observations from the initial public offering year and preceding years. Our final sample comprises 19,360 firm–year observations.

The company data are sourced from the China Stock Market and Accounting Research (CSMAR) database, the Chinese Research Data Services platform (CNRDS) platform and the WIND database. Green patent data are obtained from the State Intellectual Property Office and climate data are sourced from the China Meteorological Administration. We winsorize all continuous variables at the 1st and 99th percentiles.

4.2. Variables and model

4.2.1. Independent variable

Climate risk (*Crisk*) is the core independent variable in this paper. First, we use daily meteorological data from weather stations and exclude stations with fewer than 360 days of data per year. Next, we calculate geographical distances using latitude and longitude to match firms with their nearest weather stations. Finally, referring to previous studies (Duranton and Puga, 2000; Li et al., 2017; Zhao et al., 2020), we construct an indicator system comprising temperature and precipitation dimensions and comprehensively evaluate climate risk based on the entropy method.

The temperature-related sub-indicators include the number of days on which the daily maximum temperature exceeds the 95th percentile of the station's historical series; the annual average of the daily maximum temperature; the annual average of the daily minimum temperature; the number of days in a year on which the daily maximum temperature exceeds 30 °C and 33 °C; and the number of days in a year on which the daily minimum temperature is lower than 0 °C.

The precipitation-related sub-indicators include the annual average of daily precipitation, the number of days with torrential rains or more severe precipitation and the number of days on which daily precipitation exceeds the 95th percentile of the station's historical series. The specific calculation steps are as follows.

First, we perform extreme value standardization on each indicator j:

$$x'_{ijt} = \frac{x_{ijt} - \min\left(x_{jt}\right)}{\max\left(x_{jt}\right) - \min\left(x_{jt}\right)} \tag{1}$$

Second, the proportion of indicator j for firm i in year t is:

$$y_{ijt} = \frac{x'_{ijt}}{\sum_{i=1}^{m} x'_{ijt}} (0 \leq y_{ijt} \leq 1) \tag{2}$$

Third, the information entropy formula for indicator j is:

$$e_{jt} = -\frac{1}{\ln n} \sum_{i=1}^{n} y_{ijt} \ln y_{ijt} \tag{3}$$

Fourth, the weight of indicator j is:

$$w_{jt} = \frac{d_{jt}}{\sum_{j=1}^{k} d_{jt}}, d_{jt} = 1 - e_{jt} \tag{4}$$

Fifth, the final formula for calculating climate risk is:

$$Crisk_{it} = \sum_{j=1}^{k} y_{ijt} w_{jt} \tag{5}$$

The higher the value of $Crisk_{it}$, the greater the climate risk faced by firm i in year t. To maintain dimensional consistency, we multiply *Crisk* by 100.

4.2.2. Dependent variable

We measure corporate green innovation using the logarithm of green invention patent applications (*GI*) in the subsequent year, following Wurlod and Noailly (2018). First, climate risk has a lagged impact on business decisions, as it takes time for firms to prepare for green innovations after perceiving risk. Therefore, using the number of patent applications in the subsequent year more accurately reflects the actual impact. Furthermore, invention patents represent a high level of technological advancement and are the most challenging to obtain, making them a superior indicator of a firm's green innovation quality.

4.2.3. Control variables

Following Quan et al. (2023) and Cheng et al. (2024), we include the following control variables in our model: firm size (*Size*), return on total assets (*Roa*), gearing ratio (*Lev*), corporate cash flow (*Cash*), age of the firm (*Age*), property rights (*Soe*), executive shareholding ratio (*Gsha*), concurrent chairman and managing director (*Dual*), total asset turnover ratio (*Turn*), ratio of intangible assets (*Intan*), sales expense ratio (*Agen*) and number of employees (*Employe*). In addition, to account for disturbances caused by regional temperature variations, we control for anomalous temperatures at the province level (*Abnorm*). Referring to He et al. (2024), we apply the following formula to calculate the provincial anomalous temperature:

$$Abnorm_{pt} = Mon\_abnorm_{pt}/12 \tag{6}$$

Table 1
Variable definition.

variable	definition	Calculation
GI	Corporate green innovation	the logarithm of one plus the sum of green invention patent applications
Crisk	Climate risk	Using the entropy method to construct a comprehensive measure based on nine sub-indicators related to temperature and precipitation. See the main text for details.
Size	firm size	the logarithm of one plus the sum of total assets
Roa	return on total assets	net profit divided by total assets
Lev	gearing ratio	total liabilities divided by total assets
Cash	corporate cash flow	cash balance divided by total assets
Age	firm age	the logarithm of one plus the number of years since the company's establishment
Soe	property rights	a dummy variable, which takes 1 when the firm is state-owned, and 0 otherwise
Gsha	executive shareholding ratio	shares held by executives divided by total shares
Dual	chairman and managing director concurrently	a categorical variable that equals 1 if the chairman and CEO are the same person, and 2 otherwise
Turn	total asset turnover ratio	net sales revenue divided by average total assets
Intan	ratio of intangible assets	intangible assets divided by total assets
Agen	sales expense ratio	sale expenses divided by operating revenue
Employe	employee size	the logarithm of one plus the sum of employees
Abnorm	Provincial anomalous temperatures	see formula (6)

where p denotes the province, t denotes the year and Mon_abnorm_{pt} is the monthly mean temperature deviation for province p in year t. This deviation is calculated as the current temperature in the month in the province minus the average temperature for the same month over the past 10 years.

The specific definitions of and methods of calculating the above variables are shown in Table 1 below.

Table 2 below displays the summary statistics. The mean value of green invention patent applications (*GI*) is 0.793, with a range of 0 to 7.618, indicating a significant gap in green patent applications across firms. The mean value of climate risk (*Crisk*) is 0.175, ranging from 0.0326 to 0.935, suggesting considerable variation in climate risk across regions.

4.2.4. Model construction

To empirically test the impact of climate risk on corporate green innovation, we construct the following model:

$$GI_{i,t+1} = \beta_0 + \beta_1 Crisk_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \tag{7}$$

where i denotes the firm and t denotes the year; *GI* is the logarithm of green invention patent applications for firm i in year t + 1; Crisk is a comprehensive measure of climate risk based on the entropy method; and β_1 is the coefficient of interest. Across all specifications, we employ year, industry and province fixed effects and robust standard errors.

5. Empirical results

5.1. Baseline results

Table 3 displays the baseline regression results. As we progressively add control variables and fixed effects across columns, the coefficient of *Crisk* remains positive and statistically significant. As shown in Column (3), a one standard deviation increase in climate risk is associated with approximately a 2.1 % increase in green invention patent applications, which is also economically meaningful. These findings suggest that greater climate risk is associated with more green innovation, thereby supporting H1.

5.2. Mechanism tests

5.2.1. Intensity of government environmental regulations

The Porter hypothesis posits that appropriately designed environmental regulations can drive firms to promote green innovation to obtain compensatory benefits that offset compliance costs (Porter & van der Linde, 1995). Given climate change and the pressing need for climate governance, governments at all levels are likely to implement increasingly strict regulatory policies (Reid & Toffel, 2009). Li et al. (2024) focus on the impact of peer effects on climate risk information disclosure, revealing that cost–benefit considerations lead to active imitation, while institutional pressures result in passive imitation. Green innovation not only reduces firms' reliance on traditional, inefficient production methods but also helps them to achieve energy savings and emissions reductions, thereby generating social benefits and enhancing corporate reputation (Olsen et al., 2014). Under market-based regulations, firms incur additional costs for emitting pollutants, leading to higher product prices and reduced competitiveness. Based on cost–benefit principles, firms are incentivized to actively promote green innovation to mitigate the costs imposed by environmental policies and establish a new green competitive advantage.

Studies note that the three models in three-step mediation effect tests may suffer from three endogeneity problems, making them significantly flawed (Aguinis et al., 2017; Pieters, 2017). To further explore the mediating role of external government environmental regulation intensity, we employ a four-stage mediation effect model, referring to Aguinis et al. (2017). This model is shown below:

$$ER_{i,t} = \beta_0 + \beta_1 Crisk_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \tag{8}$$

$$GI_{i,t+1} = \beta_0 + \beta_1 ER_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \tag{9}$$

Table 2
Summary statistics.

Variable	Obs	Mean	Std	Min	Lower quartile	Median	Upper quartile	Max
GI	19,360	0.793	1.191	0.000	0.000	0.000	1.386	7.618
Crisk	19,360	0.175	0.168	0.0326	0.0640	0.116	0.212	0.935
Size	19,360	22.14	1.347	19.044	21.191	21.949	22.881	26.999
Roa	19,360	0.038	0.057	−0.375	0.014	0.036	0.064	0.216
Lev	19,360	0.444	0.210	0.051	0.275	0.443	0.606	0.999
Cash	19,360	0.163	0.128	0.006	0.074	0.126	0.213	0.695
Age	19,360	2.173	0.731	0.693	1.609	2.303	2.773	3.296
Soe	19,360	0.430	0.495	0	0	0	1	1
Gsha	19,360	0.059	0.132	0.000	0.000	0.000	0.032	3.002
Dual	19,360	1.757	0.429	1	2	2	2	2
Turn	19,360	0.691	0.589	0.001	0.365	0.563	0.837	12.373
Intan	19,360	0.047	0.051	0.000	0.016	0.034	0.058	0.323
Agen	19,360	0.067	0.080	0.000	0.020	0.041	0.082	0.478
Employe	19,360	7.700	1.352	2.079	6.852	7.657	8.504	13.22
Abnorm	19,360	0.424	0.310	0.014	0.194	0.360	0.581	1.588

$$GI_{i,t+1} = \beta_0 + \beta_1 Crisk_{i,t} + \beta_2 ER_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \quad (10)$$

Research shows that governments' collection of sewage charges, one of the key instruments of market-based environmental regulation, is more effective than administrative penalties, such as fines, in incentivizing enterprises to invest in green innovation projects (Blackman et al., 2018). Therefore, this paper measures external environmental regulatory intensity (*ER*) using sewage charges collected by provincial governments. The relevant data come from the China Tax Yearbook and China Statistical Yearbook. Strengthening environmental pollution penalties, particularly through the collection of sewage charges and fines, represents a direct approach for local governments to carry out environmental governance. Specifically, given that the total amount of sewage charges collected is closely related to the local economy, we measure *ER* by calculating the ratio of sewage charges collected by the provincial government to annual GDP. A higher ratio indicates stronger enforcement of government environmental regulations. The remaining variables in models (8)–(10) are consistent with those in model (7).

We present the regression results in Table 4. In Column (1), *Crisk* has a statistically significant impact, yielding a coefficient of 0.048. This indicates that higher climate risk in the firms' office locations corresponds to more intense local government environmental regulations. The results in Column (2) demonstrate that government environmental regulations exhibit a significant positive effect on corporate green innovation. In Column (3), *Crisk* and *ER* are positive and significant predictors of corporate green innovation. This finding supports H1a, according to which climate risk enhances governmental efforts to increase regulatory intensity, thereby encouraging firms to engage in green innovation.

5.2.2. Corporate environmental responsibility awareness

Regarding internal incentives, we assert that climate risk enhances corporate environmental responsibility awareness, thereby promoting green innovation. First, climate risk compels companies to reassess their long-term development strategies (Albitar et al., 2023). Thus, enhancing environmental responsibility awareness and investing in green innovation emerge as strategic choices to ensure sustainable development. This long-term mindset encourages companies to proactively increase their investment in R&D for green technologies and environmentally friendly solutions.

Second, as societal concern for environmental issues continues to rise, a firm's environmental performance is becoming increasingly important to its brand image and reputation (Olsen et al., 2014). Firms that demonstrate greater awareness of their environmental responsibility tend to enjoy a better reputation with consumers, investors and other stakeholders. This reputational effect incentivizes companies to intensify their

Table 3
Baseline results.

Variable	(1)	(2)	(3)
	GI	*GI*	*GI*
Crisk	0.096**	0.111***	0.100**
	(2.33)	(2.94)	(2.25)
Size	0.354***	0.370***	0.356***
	(38.87)	(37.10)	(35.93)
Roa	0.266**	0.598***	0.598***
	(2.19)	(4.97)	(4.98)
Lev	−0.004	0.032	0.083*
	(−0.08)	(0.73)	(1.90)
Cash	0.494***	0.365***	0.321***
	(8.18)	(6.28)	(5.52)
Age	−0.144***	−0.016	0.002
	(−12.75)	(−1.42)	(0.17)
Soe	−0.009	0.058***	0.051***
	(−0.51)	(3.58)	(3.06)
Gsha		0.003	−0.038
		(0.06)	(−0.67)
Dual		−0.096***	−0.090***
		(−5.57)	(−5.21)
Turn		0.025**	0.005
		(2.16)	(0.48)
Intan		0.252**	0.142
		(2.04)	(1.15)
Agen		0.191**	0.219**
		(2.06)	(2.36)
Employe		0.045***	0.048***
		(5.76)	(6.08)
Abnorm		−0.015	0.016
		(−0.72)	(0.65)
Constant	−6.842***	−7.715***	−7.480***
	(−36.06)	(−40.71)	(−40.07)
Year Fe	Yes	Yes	Yes
Industry Fe	No	Yes	Yes
Province Fe	No	No	Yes
Adjusted R^2	0.309	0.432	0.441
Observation	19,360	19,360	19,360

Note: This table primarily presents baseline regression results. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-values based on robust standard errors are in parentheses.

green innovation efforts to demonstrate environmental commitment and gain a competitive advantage in the market.

Finally, companies need to learn and adapt continuously in the face of climate risk. This process inherently enhances their environmental awareness and ability to innovate (Adrian et al., 2023). As enterprises gradually accumulate experience and knowledge of the process of responding to climate change, they become better equipped to identify opportunities and potential benefits associated with green innovation. This organizational learning process reinforces corporate environmental responsibility awareness and provides internal motivation and capacity support for sustained green innovation.

Consistent with the above, we construct the following models for the mechanism test:

$$Grinv_{i,t} = \beta_0 + \beta_1 Crisk_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \tag{11}$$

$$GI_{i,t+1} = \beta_0 + \beta_1 Grinv_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \tag{12}$$

Table 4
Strengthening government environmental regulation.

Variable	(1) *ER*	(2) *GI*	(3) *GI*
Crisk	0.048**		0.095**
	(2.21)		(2.08)
ER		0.020**	0.019**
		(2.03)	(2.02)
Size	−0.017**	0.349***	0.349***
	(−2.16)	(34.62)	(34.63)
Roa	−0.003	0.608***	0.609***
	(−0.03)	(4.96)	(4.97)
Lev	0.086**	0.088**	0.090**
	(2.37)	(2.00)	(2.04)
Cash	−0.099**	0.330***	0.329***
	(−2.09)	(5.60)	(5.57)
Age	−0.023***	0.005	0.006
	(−2.59)	(0.45)	(0.48)
Soe	−0.008	0.044***	0.045***
	(−0.62)	(2.59)	(2.64)
Gsha	−0.059	−0.052	−0.050
	(−1.51)	(−0.91)	(−0.87)
Dual	−0.018	−0.091***	−0.091***
	(−1.40)	(−5.17)	(−5.19)
Turn	0.001	0.006	0.006
	(0.09)	(0.52)	(0.51)
Intan	0.177	0.134	0.137
	(1.48)	(1.06)	(1.09)
Agen	0.090	0.213**	0.207**
	(1.00)	(2.26)	(2.20)
Employe	0.007	0.051***	0.051***
	(1.00)	(6.42)	(6.41)
Abnorm	0.319***	0.009	0.009
	(16.98)	(0.34)	(0.36)
Constant	2.989***	−7.417***	−7.438***
	(21.10)	(−38.59)	(−38.65)
Year Fe	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes
Province Fe	Yes	Yes	Yes
Adjusted R^2	0.887	0.421	0.422
Observation	18,630	18,630	18,630

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-values based on robust standard errors are in parentheses.

$$GI_{i,t+1} = \beta_0 + \beta_1 Crisk_{i,t} + \beta_2 Grinv_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \quad (13)$$

Following Jiang et al. (2024), we use the logarithm of the green investor shareholding ratio to measure corporate environmental responsibility awareness (*Grinv*). Specifically, we obtain the Fund Subject Information Table and the Stock Investment Detail Table from CSMAR's fund market series and match these two datasets to obtain fund investment details for A-share listed companies. We then determine the "investment objective" and "investment scope" of each fund by examining relevant keywords. If keywords related to a fund's investment include "environmental protection," "ecology," "green," and "new energy development," among others, the firm is recognized as a green investor. The remaining variables in models (11)–(13) are consistent with those in model (7).

Table 5 presents the regression results for models (11)–(13). In Column (1), the coefficient of *Crisk* is positive and statistically significant at the 10 % level, indicating that climate risk can increase a company's shareholding ratio of green investors, thereby strengthening internal environmental responsibility awareness. Additionally, in Column (2), the coefficient of *Grinv* is positive and statistically significant at the 1 % level, and in Column (3), the coefficients of *Crisk* and *Grinv* are both positive and statistically significant at the 1 % level. These findings suggest that climate risk to some extent stimulates corporate green innovation by enhancing firms' environmental responsibility awareness.

Table 5
Strengthening corporate environmental responsibility awareness.

Variable	(1)	(2)	(3)
	Greinv	*GI*	*GI*
Crisk	0.067*		0.012***
	(1.84)		(2.59)
Greinv		0.153***	0.152***
		(12.23)	(12.20)
Size	0.203***	0.346***	0.346***
	(25.75)	(31.49)	(31.54)
Roa	2.804***	0.365***	0.366***
	(23.42)	(2.67)	(2.68)
Lev	0.012	0.080	0.082*
	(0.35)	(1.64)	(1.67)
Cash	0.219***	0.287***	0.285***
	(4.63)	(4.53)	(4.50)
Age	0.022**	−0.014	−0.014
	(2.33)	(−1.18)	(−1.14)
Soe	−0.099***	0.082***	0.083***
	(−7.25)	(4.56)	(4.61)
Gsha	0.055	−0.014	−0.011
	(1.08)	(−0.23)	(−0.19)
Dual	−0.034**	−0.080***	−0.081***
	(−2.43)	(−4.36)	(−4.40)
Turn	0.018*	−0.003	−0.004
	(1.74)	(−0.28)	(−0.29)
Intan	0.349***	0.031	0.038
	(3.24)	(0.24)	(0.29)
Agen	0.313***	0.222**	0.215**
	(3.61)	(2.23)	(2.15)
Employe	0.016**	0.054***	0.054***
	(2.45)	(6.12)	(6.13)
Abnorm	−0.007	0.012	0.013
	(−0.36)	(0.46)	(0.48)
Constant	−4.381***	−7.307***	−7.340***
	(−29.99)	(−35.35)	(−35.45)
Year Fe	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes
Province Fe	Yes	Yes	Yes
Adjusted R^2	0.247	0.455	0.455
Observation	17,603	17,603	17,603

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-values based on robust standard errors are in parentheses.

5.3. Heterogeneity analysis

5.3.1. Corporate pollution

Polluting and non-polluting firms are also likely to differ in their coping strategies when confronted with climate risk. First, in terms of financial allocation, heavily polluting companies facing climate risk and environmental regulations need to invest large amounts in fixed assets, such as purchasing cleaner equipment and improving production processes to meet stringent emission standards. This may lead to a significant crowding-out effect on innovation funding. In contrast, non-polluting firms emit relatively few pollutants and do not need to make large-scale investments in environmental fixed assets, enabling them to spend more on green innovation activities.

Second, regarding production models, polluting firms tend to focus on traditional production models and have developed relatively fixed production processes over time, offering relatively little incentive for innovation. Non-polluting firms are usually in a more competitive market environment than their polluting counterparts and are more likely to prioritize innovation to gain a competitive edge.

Therefore, we posit that firms operating in sectors with low pollution levels exhibit a more pronounced positive response to climate risk than do their counterparts in heavily polluting industries. In 2008, the Chinese Ministry of Environmental Protection established a classification system that identified 16 sectors, including paper and leather, as high-pollution industries. We perform a binary segmentation of our sample based on this industry classification and conduct subgroup regressions. The results are displayed in Columns (1) and (2) of Table 6, respectively. The findings indicate that climate risk only promotes green innovation in non-polluting industries; its positive effect is nonsignificant in polluting industries.

Further, to test the capital expenditure characteristics of firms with different levels of pollution, we construct the following models (14) and (15):

$$RD_{i,t} = \beta_0 + \beta_1 Pollute_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \tag{14}$$

$$Facu_{i,t} = \beta_0 + \beta_1 Pollute_{i,t} + \gamma Controls_{i,t} + \sum Industry + \sum Year + \sum Province + \varepsilon_{it} \tag{15}$$

The dependent variables in models (14) and (15) are the ratio of R&D expenditures to total assets (*RD*) and the ratio of capital expenditures for fixed assets to total assets (*Facu*), respectively. The independent variable *Pollute* is a dummy variable, taking a value of 1 if the firm belongs to a polluting industry and 0 otherwise. The regression results of model (14) and model (15) are shown in Column (3) and Column (4) of Table 6. The findings indicate that polluting firms tend to invest more in fixed assets and spend less on R&D than non-polluting firms. Consequently, climate risk is less likely to promote green innovation in polluting than non-polluting firms.

5.3.2. Media attention

According to stakeholder theory, social media also play a crucial role in business operations (Lam et al., 2016). On the one hand, media attention creates strong pressure from public scrutiny (Lyon & Montgomery, 2013), stimulating corporate environmental responsibility awareness. When companies face climate risk and receive widespread media coverage, they may be more motivated to invest in green innovation to safeguard their reputation and public image. On the other hand, media reports can also convey industry dynamics and policy orientations, enabling highly attentive companies to more clearly understand the development trends and opportunities of green innovation and thus to more actively pursue green innovation activities.

Based on this theoretical framework, we argue that the stimulating effect of climate risk on green innovation is amplified in companies that attract greater attention from social media. We use financial news as a proxy for social media attention. We obtain the number of financial news articles mentioning a firm in a given year from the CNRDS database and take its logarithm to measure media attention. Next, we divide the sample into high and low media attention groups based on the sample average and conduct subgroup regressions. The results are shown in Columns (5) and (6) of Table 6, respectively. In Column (5), the coefficient of *Crisk* is positive and statistically significant at the 10 % level, but it is not significant in Column (6). This demonstrates

Table 6
Heterogeneity analysis: Corporate pollution.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Polluting industries	Non-polluting industries	R&D investment	Fixed asset investment	High media attention	Low media attention
	GI	*GI*	*RD*	*Facu*	*GI*	*GI*
Crisk	0.010	0.099*			0.012*	0.066
	(1.21)	(1.86)			(1.80)	(1.08)
pollute			−0.002**	0.009***		
			(−2.48)	(5.69)		
Size	0.334***	0.353***	−0.003***	−0.000	0.386***	0.275***
	(19.53)	(28.89)	(−12.17)	(−0.03)	(27.21)	(20.36)
Roa	0.014	0.844***	0.037***	0.078***	0.561***	0.647***
	(0.08)	(5.58)	(4.81)	(9.99)	(3.04)	(4.20)
Lev	−0.268***	0.257***	−0.003**	−0.002	−0.058	0.211***
	(−3.52)	(4.82)	(−2.16)	(−0.94)	(−0.86)	(3.80)
Cash	0.083	0.384***	0.004***	−0.036***	0.241***	0.327***
	(0.75)	(5.65)	(3.00)	(−11.97)	(2.71)	(4.32)
Age	−0.082***	0.032**	−0.002***	−0.017***	−0.002	0.009
	(−4.17)	(2.33)	(−9.99)	(−25.78)	(−0.10)	(0.57)
Soe	−0.032	0.100***	0.002	−0.003***	0.030	0.077***
	(−1.13)	(4.79)	(1.15)	(−3.04)	(1.22)	(3.28)
Gsha	−0.080	−0.014	0.002*	0.006*	−0.103	0.036
	(−0.78)	(−0.20)	(1.92)	(1.82)	(−1.12)	(0.50)
Dual	−0.049*	−0.109***	0.001**	−0.004***	−0.126***	−0.031
	(−1.66)	(−5.24)	(2.19)	(−4.32)	(−4.88)	(−1.38)
Turn	0.113***	−0.047***	0.003***	−0.006***	0.009	−0.007
	(4.84)	(−3.73)	(8.10)	(−9.47)	(0.51)	(−0.50)
Intan	−0.217	0.391***	0.016	0.085***	−0.047	0.210
	(−0.94)	(2.66)	(0.86)	(8.93)	(−0.25)	(1.30)
Agen	−0.241*	0.385***	0.030***	−0.040***	0.172	0.101
	(−1.77)	(3.04)	(11.23)	(−7.70)	(1.33)	(0.77)
Employe	0.063***	0.057***	0.002***	0.006***	0.048***	0.038***
	(3.93)	(6.23)	(3.66)	(11.25)	(4.20)	(3.68)
Abnorm	0.071*	−0.006	0.000	−0.000	0.003	0.003
	(1.68)	(−0.22)	(0.35)	(−0.01)	(0.09)	(0.10)
Constant	−6.991***	−7.530***	0.070***	0.057***	−8.036***	−5.740***
	(–22.03)	(–32.68)	(20.31)	(5.59)	(−30.05)	(–22.48)
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes
Industry Fe	Yes	Yes	Yes	Yes	Yes	Yes
Province Fe	Yes	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.410	0.461	0.047	0.206	0.481	0.413
Observation	5825	13,535	19,360	19,357	9665	9598

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-values based on robust standard errors are in parentheses.

that when social media are more attentive to a firm, the firm is more likely to engage in green innovation, particularly under external pressure.

5.4. Robustness tests

5.4.1. Alternative independent variable

We use the entropy method to construct a comprehensive climate risk index based on nine sub-indicators related to temperature and precipitation. In the robustness test, we employ two alternative proxies for climate risk: the logarithm of the number of days with heavy rainstorms in a year (*Crisk2*) and the logarithm of the number of days with daily maximum temperatures above 33 °C in a year (*Crisk3*). The regression results are displayed in Column (1) and Column (2) of Table 7, respectively. The results indicate that the baseline conclusion holds: firms exposed to higher climate risk are more likely to engage in green innovation.

5.4.2. Alternative dependent variable

In an additional robustness test, we replace the dependent variable with the corporate R&D expenditure ratio in the subsequent year to re-examine the focal relationship. This approach aims to measure corporate innovation behavior from the perspective of R&D investment. The results, shown in Column (3) of Table 7, further confirm the robustness of our baseline results.

5.4.3. Regression with subsample

A potential concern is that specific natural disasters, rather than climate risk, might be driving the observed increase in corporate green innovation. In particular, drought, an extreme climate event, has a sudden and specific impact on production and operational activities. Firms may face challenges such as water scarcity, damage to production facilities and disruption of supply chains (Muthulingam et al., 2022), potentially interfering with their normal production and operational decisions, including green innovation activities. To address this issue, we manually collect data on drought events in the cities where our sample firms are located from 2006 to 2020 and exclude these observations.

Additionally, China's four directly controlled municipalities (Beijing, Shanghai, Tianjin and Chongqing) differ significantly from other provinces in their economic, political, demographic, cultural and social structures, which may introduce confounding effects. Therefore, we exclude observations from these municipalities and re-estimate model (7).

As shown in Columns (4)–(5) of Table 7, the coefficients are similar to the baseline results, thus confirming the robustness of our findings.

5.4.4. Alternative model specification

As the dependent variable in this paper contains some zero values, we next employ a tobit model to perform a robustness test. The results are shown in Column (6) of Table 7. The coefficient of *Crisk* remains positive and statistically significant at the 1 % level, indicating that the baseline regression findings are robust.

5.4.5. Incorporating interaction fixed effects between provinces and years

China is a vast country, characterized by significant inter-provincial differences in economic development, industrial structure and policy orientation, differences that also evolve over time. We conduct a robustness test by incorporating province–year fixed effects to further mitigate potential distortion from omitted variable bias. The empirical results, shown in Column (7) of Table 7, indicate that H1 holds.

6. Conclusion

This paper examines the impact of climate risk on corporate green innovation. We find that firms facing higher climate risk tend to apply for more green invention patents. Mechanism analysis indicates that climate risk stimulates green innovation by enhancing both external local environmental regulations and internal corporate environmental responsibility awareness. These effects are more pronounced when firms operate in non-polluting (vs. polluting) industries and receive greater attention from social media.

Table 7
Robustness checks.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Alternative independent variable		Alternative dependent variable	Regression with subsample		Alternative model specification	Alternative fixed effects
	GI	*GI*	*GIRd*	*GI*	*GI*	*GI*	*GI*
Crisk			0.003*	0.010**	0.097**	0.025***	0.099**
			(1.69)	(2.24)	(2.10)	(2.59)	(2.19)
Crisk2	0.033**						
	(2.25)						
Crisk3		0.028***					
		(3.09)					
Size	0.356***	0.356***	−0.001***	0.358***	0.311***	0.675***	0.356***
	(35.92)	(35.93)	(−2.85)	(35.73)	(27.73)	(29.41)	(35.58)
Roa	0.598***	0.597***	0.009	0.597***	0.646***	1.576***	0.598***
	(4.99)	(4.97)	(1.14)	(4.94)	(4.89)	(5.31)	(4.88)
Lev	0.081*	0.078*	−0.023***	0.093**	0.211***	0.169	0.087**
	(1.86)	(1.80)	(−10.99)	(2.13)	(4.62)	(1.64)	(1.98)
Cash	0.325***	0.323***	0.025***	0.317***	0.458***	0.538***	0.327***
	(5.57)	(5.54)	(6.96)	(5.39)	(6.97)	(3.98)	(5.52)
Age	0.001	0.000	−0.003***	−0.000	0.031**	−0.092***	−0.001
	(0.07)	(0.03)	(−5.21)	(−0.03)	(2.47)	(−3.71)	(−0.08)
Soe	0.052***	0.052***	−0.001	0.046***	0.017	0.187***	0.053***
	(3.09)	(3.12)	(−1.17)	(2.73)	(0.88)	(4.98)	(3.11)
Gsha	−0.041	−0.036	0.003	−0.034	−0.036	0.071	−0.045
	(−0.72)	(−0.63)	(0.99)	(−0.60)	(−0.58)	(0.58)	(−0.78)
Dual	−0.090***	−0.089***	−0.002**	−0.091***	−0.107***	−0.150***	−0.092***
	(−5.20)	(−5.16)	(−2.43)	(−5.25)	(−5.63)	(−4.20)	(−5.26)
Turn	0.006	0.006	−0.010***	0.003	0.018	0.019	0.005
	(0.51)	(0.58)	(−13.02)	(0.25)	(1.44)	(0.62)	(0.45)
Intan	0.142	0.141	0.009	0.186	−0.027	0.031	0.150
	(1.16)	(1.15)	(1.22)	(1.49)	(−0.21)	(0.10)	(1.20)
Agen	0.224**	0.233**	0.077***	0.211**	0.294***	0.039	0.224**
	(2.41)	(2.52)	(12.86)	(2.25)	(2.73)	(0.16)	(2.38)
Employe	0.048***	0.048***	−0.001*	0.046***	0.037***	0.109***	0.049***
	(6.09)	(6.15)	(−1.71)	(5.86)	(4.25)	(5.14)	(6.16)
Abnorm	0.021	0.013	0.001	0.016	0.030	0.032	\
	(0.87)	(0.51)	(0.94)	(0.64)	(1.16)	(0.57)	\
Constant	−7.472***	−7.552***	0.094***	−7.503***	−6.529***	−16.701***	−7.474***
	(−40.05)	(−39.88)	(11.56)	(−39.77)	(−31.19)	(−39.33)	(−39.77)
Year Fe	Yes	Yes	Yes	Yes	Yes	Yes	No
Industry Fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province Fe	Yes	Yes	Yes	Yes	Yes	Yes	No
Province#Year Fe	No	No	No	No	No	No	Yes

Table 7 (*continued*)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Alternative independent variable		Alternative dependent variable	Regression with subsample		Alternative model specification	Alternative fixed effects
	GI	*GI*	*GIRd*	*GI*	*GI*	*GI*	*GI*
Adjusted R^2/ Pseudo R^2	0.441	0.441	0.447	0.443	0.403	0.209	0.437
Observation	19,360	19,360	12,106	19,021	15,356	19,360	19,348

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; t-values based on robust standard errors are in parentheses; The Tobit model uses Maximum Likelihood Estimation (MLE), and Column (6) shows the pseudo R^2; in Column (7), due to multicollinearity, *Abnorm* was omitted.

These findings have important implications for governments, listed companies and market investors. First, governments should pay more attention to the potential economic impacts of climate risk and implement appropriate measures to guide market participants toward proactive climate risk mitigation. Our findings show that as climate risk increases, firms tend to intensify their green innovation efforts.

Second, green innovation plays a crucial role in mitigating operational risk and supporting the stable and sustainable development of firms. This study finds that increasing climate risk intensifies the strength of environmental regulations, which significantly impacts corporate production and operations. Therefore, firms are advised to develop a sound strategic plan for green transformation and long-term adaptation in response to climate risk.

Lastly, increased public attention to climate issues can encourage firms to accelerate their green innovation efforts in response to climate risk. We find that social media play a moderating role in the positive relationship between climate risk and corporate green innovation. This suggests that external societal focus on climate issues provides strong incentives for firms, encouraging them to pursue long-term strategic adaptation measures to address climate risk even as they pursue short-term objectives. Such attention creates a virtuous cycle, making firms more resilient and sustainable and better positioned to generate long-term value.

Declaration of interests

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.

Appendix.

Table A1

Examples of corporate green invention patents[1].

applicant	year	public number	patent name	Keywords related to climate risk
Wuxi Xinchenke Environmental Engineering Technology Co., Ltd.	2024	CN119258753A	Waste gas purification equipment for carbon dioxide recovery	Carbon dioxide purification
Anqing Dibo Powder Metallurgy Co., Ltd.	2024	CN118912942A	Mesh belt furnace industrial exhaust gas treatment device	Industrial waste gas treatment
Shaanxi Lu Huan Environmental Protection Engineering Co., Ltd.	2024	CN222641659U	Exhaust gas desulphurization device	desulphurization
Yangzhou Hecheng Environmental Protection Equipment Co., Ltd.	2024	CN118998762A	Multi-chamber regenerative organic waste gas incineration	particulate matter
Huaneng Qufu Cogeneration Co., Ltd.	2024	CN119582704A	Clean energy generators	clean energy
Rudong Tianjian New Energy Equipment Co., Ltd.	2024	CN118783873A	Renewable clean energy photovoltaic power generation equipment	photovoltaic power generation
Changshu Xiexin Environmental Protection Technology Co., Ltd.	2024	CN118558091A	Energy efficient and environmentally friendly dust removal equipment	eliminate dust

(*continued*)

applicant	year	public number	patent name	Keywords related to climate risk
Beijing Municipal Fourth Construction Engineering Co., Ltd.	2024	CN115253549A	Energy-saving automatic sprinkler system	solar energy
China Construction 7th Bureau Second Construction Co., Ltd.	2024	CN119373265A	Low-carbon, energy-efficient green roofs for buildings	Energy emissions
Weifang Youte Inspection Service Co., Ltd.	2024	CN119263385A	Industrial wastewater treatment and purification device	wastewater treatment

[1]Information source: https://pss-system.cponline.cnipa.gov.cn/conventionalSearch.

References

Addoum, J.M., Ng, D.T., Ortiz-Bobea, A., 2023. Temperature shocks and industry earnings news. J. Financ. Econ. 150 (1), 1–45. https://doi.org/10.1016/j.jfineco.2023.07.002.

Adrian, C., Garg, M., Pham, A.V., Phang, S.-Y., Truong, C., 2023. Do natural disasters affect corporate tax avoidance? The case of drought. J. Bus. Ethics 186 (1), 105–135. https://doi.org/10.1007/s10551-022-05250-7.

Agostino, M., Rondinella, S., 2025. Do climate extreme events stimulate or hinder green innovation? evidence from the italian manufacturing sector. Struct. Chang. Econ. Dyn. 73, 101–111. https://doi.org/10.1016/j.strueco.2024.12.020.

Aguinis, H., Edwards, J.R., Bradley, K.J., 2017. Improving our understanding of moderation and mediation in strategic management research. Organ. Res. Methods 20 (4), 665–685. https://doi.org/10.1177/1094428115627498.

Alam, A., Du, A.M., Rahman, M., Yazdifar, H., Abbasi, K., 2022. SMEs respond to climate change: evidence from developing countries. Technol. Forecast. Soc. Chang. 185. 122087. https://doi.org/10.1016/j.techfore.2022.122087.

Albitar, K., Al-Shaer, H., Liu, Y.S., 2023. Corporate commitment to climate change: the effect of eco-innovation and climate governance. Res. Policy 52 (2). 104697. https://doi.org/10.1016/j.respol.2022.104697.

Amore, M.D., Bennedsen, M., 2016. Corporate governance and green innovation. J. Environ. Econ. Manag. 75, 54–72. https://doi.org/10.1016/j.jeem.2015.11.003.

Benincasa, E., Betz, F., Gattini, L., 2024. How do firms cope with losses from extreme weather events? Finance 84. 102508. https://doi.org/10.1016/j.jcorpfin.2023.102508.

Blackman, A., Li, Z., Liu, A.A., 2018. Efficacy of command-and-control and market-based environmental regulation in developing countries. Ann. Rev. Resour. Econ. 10 (1), 381–404. https://doi.org/10.1146/annurev-resource-100517-023144.

Chang, T.Y., Huang, W., Wang, Y., 2018. Something in the air: pollution and the demand for health insurance. Rev. Econ. Stud. 85 (3), 1609–1634. https://doi.org/10.1093/restud/rdy016.

Charpentier, A., 2008. Insurability of climate risks. The Geneva Papers on Risk and Insurance - Issues and Practice 33 (1), 91–109. https://doi.org/10.1057/palgrave.gpp.2510155.

Chavaillaz, Y., Roy, P., Partanen, A.-I., Da Silva, L., Bresson, É., Mengis, N., Chaumont, D., Matthews, H.D., 2019. Exposure to excessive heat and impacts on labour productivity linked to cumulative CO2 emissions. Sci. Rep. 9 (1), 13711. https://doi.org/10.1038/s41598-019-50047-w.

Cheng, B., Li, Z., Qiu, B., Xiong, T., 2024. Does collective decision-making promote SOEs' green innovation? evidence from China. J. Bus. Ethics 191 (3), 481–500. https://doi.org/10.1007/s10551-023-05495-w.

Ciais, P., Reichstein, M., Viovy, N., Granier, A., Ogée, J., Allard, V., Aubinet, M., Buchmann, N., Bernhofer, C., Carrara, A., Chevallier, F., De Noblet, N., Friend, A.D., Friedlingstein, P., Grünwald, T., Heinesch, B., Keronen, P., Knohl, A., Krinner, G., Valentini, R., 2005. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature 437 (7058), 529–533. https://doi.org/10.1038/nature03972.

Cyert R., & March J. (2006). Behavioral Theory of the Firm. In *Organizational Behavior 2*. Routledge.

Deng, Q., Huang, G., Li, D., Yang, S., 2024. The impact of climate risk on corporate innovation: an international comparison. J. Multinatl. Financ. Manag. 75. 100870. https://doi.org/10.1016/j.mulfin.2024.100870.

Duranton, G., Puga, D., 2000. Diversity and specialization in cities: why, where and when does it matter? Urban Stud. 37 (3), 533–555. https://doi.org/10.1080/0042098002104.

Gadenne, D.L., Kennedy, J., McKeiver, C., 2009. An empirical study of environmental awareness and practices in SMEs. J. Bus. Ethics 84 (1), 45–63. https://doi.org/10.1007/s10551-008-9672-9.

Garel, A., Petit-Romec, A., 2021. Investor rewards to environmental responsibility: evidence from the COVID-19 crisis. Finance 68. 101948. https://doi.org/10.1016/j.jcorpfin.2021.101948.

Gugler, K., Szücs, F., Wiedenhofer, T., 2024. Environmental policies and directed technological change. J. Environ. Econ. Manag. 124. 102916. https://doi.org/10.1016/j.jeem.2023.102916.
He, F., Hao, J., Lucey, B., 2024. Effects of climate risk on corporate green innovation cycles. Technol. Forecast. Soc. Chang. 205. 123447. https://doi.org/10.1016/j.techfore.2024.123447.
He, C., Zhang, Y., Schneider, A., Chen, R., Zhang, Y., Ma, W., Kinney, P.L., Kan, H., 2022. The inequality labor loss risk from future urban warming and adaptation strategies. Nature Commun. 13 (1), 3847. https://doi.org/10.1038/s41467-022-31145-2.
Hogan, D., Schlenker, W., 2024. Non-linear relationships between daily temperature extremes and US agricultural yields uncovered by global gridded meteorological datasets. Nat. Commun. 15 (1), 4638. https://doi.org/10.1038/s41467-024-48388-w.
Hou, X., Kong, S., Xiang, R., 2024. Extreme high temperatures and corporate low-carbon actions. Sci. Total Environ. 925. 171704. https://doi.org/10.1016/j.scitotenv.2024.171704.
Hu, H., Wei, W., Chang, C.-P., 2022a. Examining the impact of extreme temperature on green innovation in China: evidence from city-level data. Energy Econ. 114. 106326. https://doi.org/10.1016/j.eneco.2022.106326.
Hu, J., Wu, H., Ying, S.X., 2022b. Environmental regulation, market forces, and corporate environmental responsibility: evidence from the implementation of cleaner production standards in China. J. Bus. Res. 150, 606–622. https://doi.org/10.1016/j.jbusres.2022.06.049.
Huang, H.H., Kerstein, J., Wang, C., 2018. The impact of climate risk on firm performance and financing choices: an international comparison. J. Int. Bus. Stud. 49 (5), 633–656. https://doi.org/10.1057/s41267-017-0125-5.
Huang, X., Liu, W., Zhang, Z., Zou, X., Li, P., 2023. Quantity or quality: environmental legislation and corporate green innovations. Ecol. Econ. 204. 107684. https://doi.org/10.1016/j.ecolecon.2022.107684.
Hutchison-Krupat, J., Chao, R.O., 2014. Tolerance for failure and incentives for collaborative innovation. Prod. Oper. Manag. 23 (8), 1265–1285. https://doi.org/10.1111/poms.12092.
Ilhan, E., Krueger, P., Sautner, Z., Starks, L.T., 2023. Climate Risk Disclosure and institutional investors. Rev. Financ. Stud. 36 (7), 2617–2650. https://doi.org/10.1093/rfs/hhad002.
Jiang, Y., Ding, X., Ren, Y.S., Kong, X., Baltas, K., 2024. Low-carbon city pilot policy and green investors entry. Financ. Res. Lett. 64. 105421. https://doi.org/10.1016/j.frl.2024.105421.
Kolk, A., Pinkse, J., 2004. Market strategies for climate change. Eur. Manag. J. 22 (3), 304–314. https://doi.org/10.1016/j.emj.2004.04.011.
Krueger, P., Sautner, Z., Starks, L.T., 2020. The Importance of climate risks for institutional investors. Rev. Financ. Stud. 33 (3), 1067–1111. https://doi.org/10.1093/rfs/hhz137.
Lam, H.K.S., Yeung, A.C.L., Cheng, T.C.E., 2016. The impact of firms' social media initiatives on operational efficiency and innovativeness. J. Oper. Manag. 47, 28–43. https://doi.org/10.1016/j.jom.2016.06.001.
Li, B., Li, T., Yu, M., et al., 2017. Can equalization of public services narrow the regional disparities in China? A spatial econometrics approach. China Econ. Rev. 44, 67–78. https://doi.org/10.1016/j.chieco.2017.03.010.
Li, B., Yao, Y., Usman, M., Han, M., 2024a. How does climate risk affect corporate innovation? Evidence from China. Acc. Fin. 64 (3), 2279–2319. https://doi.org/10.1111/acfi.13215.
Li, B., Lin, Y., Lv, W., 2025. Confucianism and corporate awareness of climate change. China J. Account. Res. 100417.
Li, Y., Wang, D., Meng, D., Hu, Y., 2024b. Peer effect on climate risk information disclosure. China J. Account. Res. 17 (3). 100375.
Linnenluecke, M.K., Stathakis, A., Griffiths, A., 2011. Firm relocation as adaptive response to climate change and weather extremes. Glob. Environ. Chang. 21 (1), 123–133. https://doi.org/10.1016/j.gloenvcha.2010.09.010.
Liu, X., Yuan, X., Ge, X., Jin, Z., 2024. Adaptation and innovation: how does climate vulnerability shapes corporate green innovation in BRICS. Int. Rev. Financ. Anal. 94. 103272. https://doi.org/10.1016/j.irfa.2024.103272.
Lyon, T.P., Montgomery, A.W., 2013. Tweetjacked: the impact of social media on corporate greenwash. J. Bus. Ethics 118, 747–757. https://doi.org/10.1007/s10551-013-1958-x.
Muthulingam, S., Dhanorkar, S., Charles, J.C., 2022. Does water scarcity affect environmental performance? Evidence from manufacturing facilities in Texas. Manag. Sci. 68 (4), 2785–2805. https://doi.org/10.1287/mnsc.2021.4013.
Olsen, M.C., Slotegraaf, R.J., Chandukala, S.R., 2014. Green claims and message frames: how green new products change brand attitude. J. Mark. 78 (5), 119–137. https://doi.org/10.1509/jm.13.0387.
Ozkan, A., Temiz, H., Yildiz, Y., 2023. Climate risk, corporate social responsibility, and firm performance. Br. J. Manag. 34 (4), 1791–1810. https://doi.org/10.1111/1467-8551.12665.
Pankratz, N., Bauer, R., Derwall, J., 2023. Climate change, firm performance, and investor surprises. Manag. Sci. 69 (12), 7352–7398. https://doi.org/10.1287/mnsc.2023.4685.
Pieters, R., 2017. Meaningful mediation analysis: plausible causal inference and informative communication. J. Consum. Res. 44 (3), 692–716. https://doi.org/10.1093/jcr/ucx081.
Porter, M.E., van der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J. Econ. Perspect. 9 (4), 97–118. https://doi.org/10.1257/jep.9.4.97.
Qi, X., Wu, Z., Xu, J., Shan, B., 2023. Environmental justice and green innovation: a quasi-natural experiment based on the establishment of environmental courts in China. Ecol. Econ. 205. 107700. https://doi.org/10.1016/j.ecolecon.2022.107700.
Quan, X., Ke, Y., Qian, Y., Zhang, Y., 2023. CEO foreign experience and green innovation: evidence from China. J. Bus. Ethics 182 (2), 535–557. https://doi.org/10.1007/s10551-021-04977-z.
Reid, E.M., Toffel, M.W., 2009. Responding to public and private politics: corporate disclosure of climate change strategies. Strateg. Manag. J. 30 (11), 1157–1178. https://doi.org/10.1002/smj.796.
Ren, X., Li, W., Li, Y., 2024. Climate risk, digital transformation and corporate green innovation efficiency: evidence from China. Technol. Forecast. Soc. Chang. 209. 123777. https://doi.org/10.1016/j.techfore.2024.123777.

Rennings, K., 2000. Redefining innovation—Eco-innovation research and the contribution from ecological economics. Ecol. Econ. 32 (2), 319–332. https://doi.org/10.1016/S0921-8009(99)00112-3.

Rodima-Taylor, D., Olwig, M.F., Chhetri, N., 2012. Adaptation as innovation, innovation as adaptation: an institutional approach to climate change. Appl. Geogr. 33, 107–111. https://doi.org/10.1016/j.apgeog.2011.10.011.

Sun, Y., Shen, Y., Tan, Q., 2024. The spillover effect of customers' ESG performance on suppliers' green innovation quality. China J. Account. Res. 17 (3). 100362. https://doi.org/10.1016/j.cjar.2024.100362.

Sun, Y., Zhu, S., Wang, D., Duan, J., Lu, H., Yin, H., Tan, C., Zhang, L., Zhao, M., Cai, W., Wang, Y., Hu, Y., Tao, S., Guan, D., 2024b. Global supply chains amplify economic costs of future extreme heat risk. Nature 627 (8005), 797–804. https://doi.org/10.1038/s41586-024-07147-z.

Tian, Y., Chen, S., Dai, L., 2024. How climate risk drives corporate green innovation: evidence from China. Financ. Res. Lett. 59. 104762. https://doi.org/10.1016/j.frl.2023.104762.

Wang, C., Li, W., Li, J., Wan, L., 2024. The effects of extreme climate events on green technology innovation in manufacturing enterprises. J. Bus. Econ. Manag. 25 (2), 337–355. https://doi.org/10.3846/jbem.2024.21170.

Wang, C.H., Juo, W.-J., 2021. An environmental policy of green intellectual capital: green innovation strategy for performance sustainability. Bus. Strateg. Environ. 30 (7), 3241–3254. https://doi.org/10.1002/bse.2800.

Wang, Y., Wang, C., 2025. Climate risk and firms' R&D investment: evidence from China. Int. Rev. Econom. Fin. 104066. https://doi.org/10.1016/j.iref.2025.104066.

Wen, J., Zhao, X.-X., Fu, Q., Chang, C.-P., 2023. The impact of extreme weather events on green innovation: which ones bring to the most harm? Technol. Forecast. Soc. Chang. 188. 122322. https://doi.org/10.1016/j.techfore.2023.122322.

Wu, Y., 2025. The impact of climate risks on green technology innovation: an empirical study based on panel data of 269 cities in China. Front. Environ. Sci. 12. 1510883. https://doi.org/10.3389/fenvs.2024.1510883.

Wurlod, J.D., Noailly, J., 2018. The impact of green innovation on energy intensity: an empirical analysis for 14 industrial sectors in OECD countries. Energy Econ. 71, 47–61. https://doi.org/10.1016/j.eneco.2017.12.012.

Yan, Z., Yu, Y., Du, K., Zhang, N., 2024. How does environmental regulation promote green technology innovation? Evidence from China's total emission control policy. Ecol. Econ. 219. 108137. https://doi.org/10.1016/j.ecolecon.2024.108137.

Zhao, D., Li, C., Wang, Q., et al., 2020. Comprehensive evaluation of national electric power development based on cloud model and entropy method and TOPSIS: a case study in 11 countries. J. Clean. Prod. 277. 123190. https://doi.org/10.1016/j.jclepro.2020.123190.