

Corporate Climate Perception Risk, Supply Chain Resilience and Stock Price Collapse Risk

Jiaying Du

School of Economics, College, Shanghai University, Shanghai 200444, China

Abstract: As the trend of global warming intensifies, extreme weather events have become a significant factor affecting corporate operations and capital market stability. The climate risks faced by enterprises not only directly threaten their physical assets and supply chain stability but also indirectly influence share price volatility by affecting investor expectations and market sentiment. Supply chain resilience, as the core capability for enterprises to withstand external shocks, directly determines their risk resistance level under climate impacts. Concurrently, analysts, as information intermediaries within capital markets, exert influence through disclosure and oversight effects that shape investor perceptions and pricing of corporate climate risks. Consequently, examining how corporate climate risks transmit through supply chain resilience to stock price crash risks, while analysing the moderating role of analyst attention, holds significant theoretical and practical implications for advancing climate finance research and refining capital market risk management frameworks. Consequently, this study employs a panel data two-way fixed effects model to empirically examine the impact of corporate climate risk on stock price crash risk, the transmission mechanism involving supply chain resilience as an intermediary variable, and the role of analyst attention in this risk transmission process. The research sample comprises all listed companies on China's A-share market from 2006 to 2024. The findings reveal: (1) Firms with greater climate risk exposure face heightened stock price crash risk; (2) Climate risk amplifies stock price crash risk by undermining supply chain resilience; (3) Firms receiving greater analyst attention experience a weaker amplification effect of climate risk on stock price crash risk.

Keywords: Climate risk; Stock price crash risk; Supply chain resilience; Information asymmetry.

1. Introduction

Since the early 21st century, as the global climate governance process has deepened, the climate change crisis has become a major challenge facing all of humanity. Repeated assessment reports issued by the Intergovernmental Panel on Climate Change (IPCC) unequivocally state that greenhouse gas emissions from human activities have indisputably caused global warming and triggered unprecedented changes in the climate system. These include the frequent occurrence of extreme weather events, rising sea levels, and ecosystem imbalances, which have resulted in significant global casualties and economic losses, posing a fundamental and systemic threat to the global socio-economic system [16]. The financial risks stemming from climate change are characterised by their long-term, structural, and systemic nature, making them a focal point for banking regulators worldwide. International bodies such as the Financial Stability Board (FSB) and the Task Force on Climate-related Financial Disclosures (TCFD) have vigorously promoted the integration of climate-related risks into financial analysis and macroprudential regulatory frameworks. In June 2022, the Basel Committee on Banking Supervision (BCBS) formally issued the Principles for the Effective Management and Supervision of Climate-related Financial Risks. It provides crucial guidance for global banking institutions and regulatory authorities in identifying, measuring, and addressing climate risks.

According to estimates by the Swiss Re Institute, a global temperature rise of 2.0°C by 2050 could result in economic losses exceeding 10% of GDP worldwide [27]. The potential impacts of climate change manifest as increasingly frequent and destructive natural disasters, posing significant risks to businesses and investors and inflicting severe shocks on the

global economy. Such shocks not only impede the ongoing global transition towards a low-carbon future but also exacerbate the deterioration of the global climate and continuously elevate market risks. For micro-level business entities, climate risk shocks directly undermine the robustness of operational stability, financial performance, and market value. For listed companies, the most tangible manifestation of this impact is frequent and severe share price volatility. A significant form of risk is the risk of share price collapse, which can be understood as a precipitous decline triggered by the sudden release of accumulated negative information at a specific juncture. China's stock market, as a quintessential example of an emerging transition economy, has witnessed multiple instances of market collapse. Underlying causes primarily include market information asymmetry and agency problems, a high proportion of retail investors prone to herd behaviour, and the prevalence of speculative themes.

Academic research views stock price collapse risk not only as an extreme manifestation of information asymmetry but also as a composite reflection of distorted market efficiency and corporate governance failures. Amid heightened volatility in global capital markets, managing stock price crash risk has become a critical focus in corporate finance and investment studies. Linking climate risk with stock price crash risk represents an emerging research frontier. Early studies predominantly examined the short-term impact of environmental performance (e.g., pollution emissions) or isolated environmental incidents (e.g., oil spills) on market value in isolation. Over the past five years, research perspectives have expanded to encompass threats to capital market stability. Current research has identified several key transmission channels: Firstly, the information asymmetry channel. Climate risks involve complex long-term impacts and uncertainties, creating strong incentives for firms to

engage in “selective disclosure” or “green washing” to conceal their true climate vulnerabilities. Such information manipulation leads to the internal accumulation of negative information, laying the groundwork for future stock price collapses. Conversely, high-quality environmental disclosure has been shown to effectively reduce crash risk. Second, the material risk channel: physical and transition risks tangibly erode corporate profitability and asset values, deteriorating fundamentals. When such adverse effects exceed market expectations and are abruptly disclosed, they may trigger collapses. Thirdly, the external oversight and governance channel: auditors may increase disclosures on key audit matters due to a company's high climate risk. This can itself be viewed as a risk warning, but may also accelerate the market's digestion of negative information.

This study systematically bridges three relatively distinct research domains: climate finance, supply chain management, and corporate finance. By introducing the key mediating variable of supply chain resilience, it reveals an indirect pathway through which climate risks impact the most critical operational networks of enterprises (supply chains) thereby triggering significant volatility in capital markets. This extends the research perspective of climate finance from the dualistic “firm-market” relationship to a complex “environment-operations-market” system, providing a more refined theoretical framework for understanding the formation mechanisms and transmission processes of climate-related financial risks.

2. Literature Review

2.1. Research on Climate Risk

According to Giglio (2021) and Li (2024), climate risk is categorised into two primary types: physical risk and transition risk [11, 21]. Physical risk encompasses the threat of direct damage to productive assets caused by extreme weather events and chronic climate change. Transition risk involves potential cash flow risks arising from the shift towards a low-carbon economy, primarily influenced by policy and regulatory frameworks alongside societal expectations and pressures. Regarding physical climate risks, Guo et al. (2024) developed a composite physical climate risk index for each nation based on daily meteorological station observations, integrating four extreme events: extreme low temperatures (LTD), extreme high temperatures (HTD), extreme rainfall (ERD), and extreme drought (EDD) [12]. Magnan et al. (2021) estimated the composite risks of anthropogenic climate change by the end of the 21st century based on expert judgements from the Intergovernmental Panel on Climate Change (IPCC). They developed a scoring system to translate the IPCC's qualitative risk assessments into quantitative risk scores [23]. Regarding climate transition risk, Huynh et al. (2021) captured the covariance between bonds and climate change news index innovations as a measure of climate transition risk [14]. Xu et al. (2024) employed the Term Frequency-Inverse Document Frequency (TF-IDF) method to construct daily climate transition risk for China from 2000 to 2022 [29]. Furthermore, Li et al. (2024) conducted text analysis on earnings conference call transcripts, constructing separate dictionaries measuring ‘physical risk’ and ‘transition risk’ to comprehensively quantify corporate-level climate risk exposure [21].

As global climate governance deepens, central banks and financial regulators increasingly recognise that climate

change profoundly threatens financial stability. Firstly, extreme weather events directly impact real businesses, leading to reduced production capacity, supply chain disruptions and asset depreciation. Zhang et al. (2018) found an inverted U-shaped relationship between temperature and firm-level total factor productivity [32]. Pankratz et al. (2024) found that extreme heat increases economic risks for firms, leading to reduced corporate income and operating revenues [26]. Secondly, Francesca et al. (2021) discovered that delays in climate policy implementation and heightened inflation volatility may pose significant challenges to central banks' price stability mandates [9]. Finally, as climate risk factors become incorporated into asset pricing, climate risks may induce abnormal disturbances in relevant asset prices. Cuculiza et al. (2025) observed that stocks exhibiting higher climate sensitivity predict lower equity returns [8]. Ye et al. (2024) identified a positive correlation between extreme climate risk and bond yields [30]. Li et al. (2024) documented that enterprises with elevated climate risk exposure face substantially greater financing difficulties, increased capital costs, and more frequent and pronounced stock price volatility [21].

2.2. Research on Supply Chain Resilience

Christopher and Peck (2004) first introduced the concept of supply chain resilience, referring to its significance for business continuity and positive impact on corporate performance within the context of complex global procurement networks [6]. Currently, as no universally agreed definition of supply chain resilience exists, resilience measurement approaches vary across the literature. Jia and Li (2024) assessed the stability of corporate relationships with clients and suppliers by calculating the proportion of procurement/sales value with the top five suppliers/clients relative to total procurement/sales value across different years. They then computed the average values for upstream and downstream resilience, reflecting the overall adaptability and recovery capacity of the company's supply chain in response to external fluctuations [17]. Albuquerque et al. (2020) employed stock return volatility as a resilience metric. Greater stock return volatility indicates lower resilience [1]. Guo and Li (2025) employ the natural logarithm of the accounts receivable-to-revenue ratio to gauge capital tied up. A smaller ratio signifies less supplier capital occupied by customers, indicating more stable supply chain relationships and thus greater resilience [13].

The existing literature extensively examines the disruptive effects of external shocks on supply chains, encompassing diverse impacts such as natural disasters, public health crises, and trade frictions. It posits that external shocks not only cause supply chain disruptions but may also generate cascading effects through supply chain networks. Colicchia and Strozzi (2012) contend that the advancement of globalisation implies that corporate supply chains may span multiple nations, becoming longer and more complex, thereby diminishing resilience and heightening vulnerability to disruption when confronting risks [7]. Inoue and Todo (2019) examined two major earthquakes in Japan, finding that enterprises linked to suppliers across multiple industries were more susceptible to production losses and economic impacts, with these effects propagating to regions not directly affected by the disasters [15]. Carvalho et al. (2021) discovered that supply chain disruptions caused by natural disasters propagate both upstream and downstream along the chain,

affecting suppliers and customers at all levels of the affected enterprise, thereby causing widespread supply shortages and economic losses [4]. Scholars are now examining climate change's impact on supply chains. Ali et al. (2023) found that climate extremes positively influence agri-food supply chain resilience through the mediating role of internal and external social capital [2]. Pankratz et al. (2024) observed that high temperatures in supplier locations reduce both suppliers' and their customers' operating revenues. Furthermore, when adverse weather events in supplier locations become more frequent, companies terminate relationships with those suppliers [26]. Guo and Li (2025) found that physical climate risks significantly undermine corporate supply chain resilience [13].

2.3. Research on Stock Price Crash Risk

Within the field of finance, stock price crash risk denotes the probability of a company's share price experiencing extreme negative returns. This phenomenon is characterised by market panic selling and value destruction triggered by the concentrated release of adverse news. Academic circles have established a relatively mature theoretical framework for the formation mechanisms of stock price crash risk, centred on information asymmetry and agency conflicts. The 'information concealment hypothesis' proposed by Jin and Myers (2004) constitutes a foundational theory in this field. Due to information asymmetry, company management possesses both the motivation and capability to conceal adverse corporate news in order to preserve their positional privileges, remuneration packages, or personal reputations. When concealed negative information accumulates to a critical threshold, its 'avalanche-like' release becomes unstoppable, triggering a precipitous decline in share prices [18]. Li et al. (2023) analysed the impact of institutional investor information interactions on A-share listed companies in China's stock market through a multi-network structure approach, revealing that such interactions amplify crash risk through herd behaviour rather than oversight effects [20].

Krueger et al. (2020) found that climate risk ranked fifth in importance for investment decisions in a survey of 439 fund managers, portfolio managers, executives and managing directors [19]. This finding reflects a growing trend among academics to incorporate climate risk into the framework for financial investment decision-making. Wu et al. (2022), using a sample of Chinese listed companies, observed that enterprises experiencing climate risk events face short-term market repercussions such as share price declines, indicating investors' heightened sensitivity to climate-related risks [28]. Chen et al. (2023) established that climate policy uncertainty significantly impacts stock price volatility [5]. Ni et al. (2022) identified a significant positive correlation between climate vulnerability and the risk of corporate stock price collapse [25]. Naseer et al. (2024) observed that greater climate change risk correlates with heightened stock price volatility, while robust ESG practices substantially mitigate such volatility [24]. Gan et al. (2024) observed that, moderated by environmental news coverage, even minor shifts in external information can trigger investor panic, leading to widespread sell-offs of stocks in companies facing climate transition risks [10]. Concurrently, Lin and Wu (2023) demonstrated that climate risk disclosure effectively reduces stock crash risk [22]. Bose et al. (2025) observed a positive correlation between carbon risk and future stock crash probability, with internal and external monitoring mitigating information

asymmetry related to carbon risk to reduce crash risk [3]. Conversely, Zhang et al. (2025) found that an overly optimistic tone in climate risk disclosures tends to distort investor perceptions, thereby exacerbating stock price collapses [31].

3. Theoretical Foundations and Research Hypotheses

3.1. Theory of Information Asymmetry

The theory of information asymmetry posits that in market economic activities, sellers possess greater knowledge about goods than buyers. The party with superior information can gain market advantages by conveying reliable information to the information-poor party, thereby maintaining an informational edge. Within corporate finance, this theory manifests primarily as an uneven distribution of information between a company's internal management and external investors. As the actual operators of the enterprise, management inherently possesses private information regarding the firm's true value, operational status, and future risks, creating a propensity for opportunistic behaviour. External investors, conversely, occupy an information disadvantage, relying chiefly on publicly disclosed information for decision-making and incurring significant costs to verify the accuracy of such information. This dynamic creates an information barrier.

Information asymmetry may manifest at various stages of contract formation. Pre-contractual market failures stemming from information asymmetry are defined as adverse selection issues. Post-contractual performance risks and behavioural distortions arising from information asymmetry are categorised as moral hazard problems. In the context of stock price collapse risks, moral hazard proves more critical. As investors cannot effectively observe all managerial actions, management may conceal unfavourable 'bad news' for the company, such as failed investments, potential litigation, or climate risk exposures.

3.2. Agency Theory

Agency theory forms the theoretical bedrock of modern corporate governance, emerging from the series of conflicts arising from the separation of ownership and management rights amid waves of corporate expansion and specialised division of labour. Its core proposition lies in the fact that, due to the divergence of objectives between principals and agents and the asymmetry of information, agents may not consistently act in the principal's best interests, thereby generating agency problems.

On the one hand, as enterprises grow and diversify, their operational scope broadens and technical demands intensify. Owners are often constrained by their own energy, expertise, and managerial capacity, making it difficult to efficiently run the business alone. Introducing professional managers to oversee day-to-day operations thus becomes a practical necessity, creating the real-world demand for principal-agent relationships. Conversely, owners (principals) pursue the maximisation of long-term corporate value, prioritising asset preservation and appreciation alongside the expansion of shareholder equity. Operators (agents), however, tend to focus on their own short-term interests, such as high remuneration, in-office consumption, and personal reputation. This divergence in objectives may lead operators to make decisions contrary to the owners' wishes, such as over-

investing to expand their personal sphere of influence or neglecting long-term R&D expenditure in pursuit of short-term performance.

3.3. Research Hypotheses

Building upon the frameworks of information asymmetry theory and principal-agent theory, and drawing upon relevant research in supply chain management, information economics, and corporate finance, this subsection systematically proposes the following research hypotheses.

Corporate climate risks sow the seeds for stock price collapse by exacerbating information asymmetry and intensifying principal-agent conflicts. Climate risk identification demands high specialisation and is characterised by long-term and uncertain nature, whereby management possesses significant informational advantages and more precise internal assessments. Consequently, when corporate assets face threats from climate disasters, potential asset stranding, or supply chain disruptions, management harbours strong incentives to delay disclosure or conceal evidence of inadequate climate risk management. This stems from concerns that such negative information could trigger short-term market panic and share price declines, thereby jeopardising personal interests such as remuneration and reputation. This concealed negative climate information accumulates internally, forming an ‘information black hole.’ Once accumulated bad news surpasses a critical threshold—such as the introduction of major climate policies or significant losses from extreme weather events—it is released en masse to the market, triggering a collapse in investor confidence and a sharp decline in share prices.

H1: The higher the climate risk faced by a company, the greater its future risk of a share price collapse.

Against the backdrop of deeply integrated global value chains, supply chains have become a critical linchpin for enterprises in managing climate risks. Firstly, physical climate risks undermine supply chain stability. Extreme weather events stemming from physical risks may directly damage key suppliers' production facilities or disrupt logistics, subsequently hindering corporate production, causing delivery delays, and driving up costs. This directly impacts business performance and transmits negative signals to the market. Secondly, as global carbon regulation policies intensify, high-carbon emission segments within supply chains face greater compliance costs and transformation pressures. Supply chain nodes failing to adapt promptly may consequently lose market competitiveness or even be eliminated. Such structural shifts weaken corporate supply chain resilience; even enterprises with low internal emissions may face policy pressures due to high-emission segments within their supply chains. When supply chain resilience is compromised, operational volatility increases, and the accumulation of negative business information lays the groundwork for share price collapses. Concurrently, to maintain market confidence, management may persist in concealing the extent of climate risk impacts on the supply chain, leading to the suppression of relevant information. When the truth can no longer be concealed, this accumulated bad news is released in concentrated bursts, triggering share price collapses.

H2: Supply chain resilience mediates the relationship between corporate climate risk and stock price crash risk. Specifically, climate risk amplifies stock price crash risk by weakening corporate supply chain resilience.

Securities analysts, as vital information intermediaries in capital markets, fulfil dual roles in information mining and public oversight. Within the climate risk context, high-calibre analysts can leverage in-depth research and specialised industry knowledge to identify, interpret, and disseminate corporate climate risks earlier. This reduces information asymmetry between management and external investors, curtails management's scope for concealing adverse developments, and enables more timely and accurate market valuation of corporate worth. Simultaneously, analysts' ongoing monitoring and questioning exert potent external oversight pressure on management, compelling greater consideration of market reputation in decision-making and thereby curbing short-termism stemming from agency problems. High analyst attention may lead to earlier pricing of corporate climate risks, reducing future stock price crash risks; conversely, low attention may amplify the negative impact of climate risks, increasing crash vulnerability.

H3: Analyst attention negatively moderates the relationship between corporate climate risk and stock price crash risk.

4. Methodology

4.1. Variable Definitions

4.1.1. Corporate Climate Risk

This study employs text analysis methodology, utilising computational linguistics tools for word segmentation, word vector training, and word frequency statistics to minimise subjective bias. Firstly, a dictionary comprising 62 Chinese terms related to ‘climate risk’ within annual reports was established as the seed word set. Secondly, preprocessing of corporate annual report texts was conducted. Subsequently, to enhance the objectivity and comprehensiveness of the lexicon, a skip-gram word vector model was employed to expand the seed set by selecting terms with similarity scores exceeding 0.6. Through manual refinement, the final ‘climate risk’ lexicon comprises 140 Chinese terms. Finally, the total word frequency of the expanded terms and their ratio to the total annual report word frequency were calculated to derive the climate risk indicator, which underwent one-period lag processing. A higher indicator value indicates greater climate risk exposure for the enterprise.

4.1.2. Stock Price Crash Risk

Stock price crash risk measures the probability of extreme negative returns occurring in listed companies' share prices. The core concept underlying this indicator stems from the sudden, concentrated release of previously accumulated ‘bad news’. This paper measures stock price crash risk indicators in the Chinese stock market through the following methods:

First, using weekly return data for stock i , calculate the market-adjusted return for stock i :

$$r_{i,t} = \alpha + \beta_{1,i}r_{m,t-2} + \beta_{2,i}r_{m,t-1} + \beta_{3,i}r_{m,t} + \beta_{4,i}r_{m,t+1} + \beta_{5,i}r_{m,t+2} + \varepsilon_{i,t} \quad (1)$$

Where, $r_{i,t}$ represents the return on stock i during week t of each year, and $r_{m,t}$ denotes the market-capitalisation-weighted average return on all A-shares during week t .

The market-adjusted specific return on stock i during week t is $W_{i,t}$:

$$W_{i,t} = \ln(1 + \varepsilon_{i,t}) \quad (2)$$

Secondly, construct the following two metrics for measuring stock price crash risk.

The first metric for assessing stock price crash risk is the Negative Skewness of Returns (NCSKEW), defined as the negative skewness of a stock's weekly returns after market adjustment. When the return distribution is left-skewed, NCSKEW is negative; the higher its absolute value, the greater the crash risk.

$$\text{NCSKEW}_{i,t} = -\frac{n(n-1)^{3/2}\sum W_{i,t}^3}{(n-1)(n-2)(\sum W_{i,t}^2)^{3/2}} \quad (3)$$

The second metric for gauging the risk of a stock price collapse is the Down-to-Up Volatility (DUVOL). This captures crash risk by comparing the disparity in volatility between upward and downward phases of share price movements. A higher DUVOL value indicates significantly greater downward volatility relative to upward volatility, signalling heightened crash risk.

$$\text{DUVOL}_{i,t} = \ln\left(\frac{(n_u-1)\sum_{\text{down}} W_{i,t}^2}{(n_d-1)\sum_{\text{up}} W_{i,t}^2}\right) \quad (4)$$

Where n_u and n_d denote the number of weeks for which stock i 's weekly returns exceed or fall below the annual average, i.e. weeks of upward movement and weeks of downward movement.

Additionally, the stock price crash probability (CRASH) indicator employs the dummy variable method to determine whether an individual stock experienced extreme negative returns during a specific period. A CRASH value of 1 indicates that the stock experienced at least one crash event during that year; conversely, a CRASH value of 0 signifies that no crash event occurred.

$$\text{CRASH}_{i,t} = \begin{cases} 1, & \text{if } R_{i,t} < \mu_{i,t} - 3.09\sigma_{i,t} \\ 0, & \text{otherwise} \end{cases} \quad (5)$$

4.1.3. Supply Chain Resilience

This paper defines supply chain resilience as the capacity of an enterprise's supply chain network to withstand, adapt to, and rapidly resume operations when confronting external shocks such as climate risks. This resilience manifests through deep binding relationships between core partners and is specifically reflected in the following three dimensions:

Firstly, structural stability: equity ties and long-term contracts with core suppliers foster specialised investments in equipment, technology, processes, and personnel, such as joint innovation R&D and dedicated production lines. This enhances mutual dependency and lock-in effects, forming a robust community of shared interests between the enterprise and its core suppliers. When adverse shocks occur, both parties possess strong incentives to maintain cooperation and weather the storm together, thereby enhancing supply chain stability and resilience. Secondly, operational synergy. Grounded in long-term trust and established cooperation practices, enterprises and their core suppliers can swiftly activate emergency response mechanisms following climate events. This enables flexible resource allocation, prioritising the supply of critical materials to achieve the fastest possible production recovery. Consequently, transaction costs are significantly reduced, strengthening the supply chain's adaptability and resilience. Thirdly, information transparency. Enterprises typically establish efficient information-sharing mechanisms and joint decision-making processes with core suppliers. This ensures timely and accurate flow of information regarding potential risks, operational status, and recovery progress throughout the chain, facilitating seamless information integration. This enables management to accurately assess impacts and formulate countermeasures, thereby reducing decision delays and the accumulation of bad news caused by information asymmetry.

Accordingly, this paper employs the proportion of annual procurement expenditure allocated to the top five suppliers as a measure of supply chain concentration, serving as a proxy for supply chain resilience. When confronting external systemic shocks, a highly concentrated supply chain built upon deep collaboration typically demonstrates superior stability, coordination, and information transparency compared to a loosely integrated, low-concentration transactional supply chain. Consequently, elevated supplier concentration signifies stronger supply chain resilience for enterprises.

The definitions of the main variables in this article are shown in Table 4-1:

Table 4-1. Variable Definitions

Type	Variable	Definition
Explanatory Variable	Clrisk	Total frequency of climate risk expansion terms in corporate annual reports, processed with one-period lag.
Explained Variable	NCSKEW	The negative skewness coefficient of weekly returns adjusted by market models within the corporate year.
	DUVOL	The natural logarithm of the ratio between the standard deviation of weekly returns below the mean and the standard deviation above the mean within the corporate year.
Mediating Variable	supplier_ratio	Supply chain concentration, measured as the proportion of annual procurement expenditure allocated to upstream suppliers.
Moderating Variable	lnAnaAttention	The natural logarithm of the number of securities analysts covering the same company, incremented by one.
Control Variables	lag ROA	One-period lagged return on total assets, gauging asset utilisation efficiency and profitability.
	lag Growth	One-period lagged revenue growth rate, reflecting corporate growth trajectory and developmental potential.
	lag Size	Enterprise scale from the previous period, measured by the natural logarithm of total assets.
	lag TobinQ	Tobin's Q ratio from the previous period, gauging the ratio of market value to replacement cost to reflect investment value.
	lag annual_return	Annual stock return from the previous period, indicating the level of investment returns.
	lag_volatility	Stock price volatility from the previous period, measuring the intensity of price fluctuations.
	lag cash	Cash flow ratio from the previous period, assessing short-term debt repayment capacity and liquidity.

4.2. Model Specification

To examine the impact of corporate climate risk on stock price crash risk, this paper constructs the following panel fixed-effects model:

$$\text{CrashRisk}_{it+1} = \alpha_0 + \alpha_1 \text{Clrisk}_{it} + \sum \alpha \text{Controls}_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (6)$$

Among these, CrashRisk_{it+1} serves as the dependent variable, representing company i stock price crash risk in period $t+1$, measured using either NCSKEW or DUVOL. Clrisk_{it} denotes company i climate risk exposure in period t . The model simultaneously controls for firm-specific fixed effects and year fixed effects, employing robust standard errors clustered at the firm level to address potential serial correlation and heteroskedasticity issues.

To investigate the mediating effect of supply chain resilience, the following mediation model is constructed:

$$\text{Resilience}_{it} = \beta_0 + \beta_1 \text{Clrisk}_{it} + \sum \beta \text{Control}_{sit} + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

Where Resilience_{it} is the mediating variable, representing the supply chain resilience of firm i in period t , measured using the supplier concentration ratio.

To examine the moderating effect of analyst attention, the following moderation model is constructed:

$$\text{CrashRisk}_{it+1} = \alpha_0 + \alpha_1 \text{Clrisk}_{it} + \alpha_2 \text{Clrisk}_{it} \times W + \varepsilon_{it} \quad (8)$$

Here, W denotes the moderator variable, measured using the analyst attention.

4.3. Sample Selection and Data Sources

This study selected Chinese A-share listed companies from 2006 to 2024 as the initial research sample. The sample screening process was as follows: (1) Exclusion of companies in the financial sector; (2) Exclusion of companies classified as ST, *ST, or those that had been delisted; (3) Exclusion of samples with missing key variable data. Following these adjustments, 47,562 firm-year observations were ultimately obtained. The data utilised in this study were sourced from multiple databases: corporate financial data, corporate governance data, stock transaction data, and supply chain data were all obtained from CSMAR and Wind database.

5. Results and discussion

5.1. Descriptive Statistics

Descriptive statistics for the primary variables are presented first, with results shown in Table 5-1.

Table 5-1. Descriptive Statistics

Variable	N	Mean	SD	p50	Min	Max
NCSKEW	47562	-0.299	0.695	-0.262	-2.375	1.545
DUVOL	47562	-0.195	0.483	-0.196	-2.532	3.511
supplier_ratio	38073	18.86	16.05	13.53	2.133	81
Clrisk	47562	4.241	0.989	4.263	1.792	6.641
lag ROA	47562	0.036	0.068	0.036	-0.249	0.221
lag Growth	47562	0.161	0.423	0.099	-0.607	2.703
lag Size	47562	22.21	1.444	21.97	19.59	27.27
lag TobinQ	47562	1.973	1.271	1.557	0.843	8.391
lag annual_return	47562	0.138	0.460	0.050	-0.682	1.756
lag_volatility	47562	44.25	20.71	39.68	13.86	122.5
lag cash	47562	0.047	0.072	0.046	-0.177	0.251

The mean values for the two proxy indicators of stock price crash risk, NCSKEW and DUVOL, are -0.299 and -0.195 respectively, both negative figures. This aligns with the well-established fact of left skewness in stock returns within financial markets. Concurrently, both indicators exhibit substantial standard deviations and wide ranges, indicating significant variation in stock price crash risk across the sample firms. The climate risk indicator displays a standard deviation of 0.989, with minimum and maximum values of 1.792 and 6.641 respectively. This demonstrates marked heterogeneity in climate risk exposure among different enterprises.

The mean of the supply chain resilience proxy variable supplier_ratio is 18.86%, with a median of 13.53%. This indicates that the mean is influenced by firms with highly concentrated supply chains, resulting in a right-skewed distribution. Its standard deviation reached 16.05, with a maximum value of 81%, indicating substantial variation in supply chain structure and stability among the sample firms. Descriptive statistics for all other control variables fell within reasonable ranges, broadly consistent with existing literature findings, suggesting the sample data possesses sound

representativeness.

5.2. Correlation Analysis

Table 5-2 reports the Pearson correlation coefficient matrix between primary variables, aiming to preliminarily explore relationships and test for multicollinearity. Clrisk exhibits positive correlations with NCSKEW and DUVOL at 0.020 and 0.018 respectively, both statistically significant at the 1% level. This preliminarily indicates that firms facing higher climate risks also exhibit elevated future stock price crash risks. This finding provides preliminary univariate evidence supporting the core research hypothesis of this paper.

As anticipated, the correlation coefficient between NCSKEW and DUVOL is as high as 0.873 and significant at the 1% level, demonstrating that the two indicators possess high internal consistency and can reliably measure the same underlying concept. Examining correlations among explanatory variables reveals that, with few exceptions, the absolute values of correlation coefficients between most control variables fall well below the empirical threshold of 0.7. This suggests no severe multicollinearity issues exist within the model, permitting progression to multivariate

regression analysis.

Table 5-2. Correlation Analysis

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) NCSKEW	1.000									
(2) DUVOL	0.873*	1.000								
	(0.000)									
(3) Clrisk	0.020*	0.018*	1.000							
	(0.000)	(0.000)								
(4) lag_ROA	0.018*	0.003	-0.018*	1.000						
	(0.000)	(0.563)	(0.000)							
(5) lag_Growth	0.019*	0.004	-0.030*	0.251*	1.000					
	(0.000)	(0.338)	(0.000)	(0.000)						
(6) lag_Size	-0.028*	-0.047*	0.384*	0.022*	0.028*	1.000				
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)					
(7) lag_TobinQ	0.074*	0.066*	-0.152*	0.142*	0.058*	-0.366*	1.000			
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)				
(8) lag_annual_return	0.035*	0.014*	-0.174*	0.107*	0.084*	-0.098*	0.123*	1.000		
	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)			
(9) lag_volatility	-0.048*	-0.061*	-0.152*	-0.036*	0.060*	-0.224*	0.228*	0.450*	1.000	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
(10) lag_cash	0.019*	0.010*	0.031*	0.396*	0.051*	0.049*	0.086*	0.086*	-0.037*	1.000
	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	

* denotes significance at the 5% level or better.

5.3. Benchmark Regression Analysis

Table 5-3. Benchmark Regression Analysis

	(1)	(2)	(3)	(4)
	NCSKEW	NCSKEW	DUVOL	DUVOL
Clrisk	0.024***	0.028***	0.009*	0.012**
	(0.007)	(0.007)	(0.005)	(0.005)
lag_ROA		-0.089		-0.061
		(0.067)		(0.045)
lag_Growth		0.014*		0.003
		(0.008)		(0.006)
lag_Size		0.033***		0.014***
		(0.007)		(0.005)
lag_TobinQ		0.066***		0.041***
		(0.004)		(0.003)
lag_annual_return		0.061***		0.015**
		(0.011)		(0.007)
lag_volatility		-0.002***		-0.001***
		(0.000)		(0.000)
lag_cash		-0.075		-0.057
		(0.056)		(0.038)
_cons	-0.399***	-1.200***	-0.231***	-0.595***
	(0.030)	(0.161)	(0.021)	(0.108)
Firm_FE	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes
N	47562	47562	47562	47562
r2_a	0.073	0.080	0.080	0.086
F	11.001	41.592	3.044	31.282

Note: The standard errors for company-level clustering are shown in brackets. ***, ** and * denote statistical

significance at the 1%, 5% and 10% levels respectively. The same symbols apply to the tables below.

Table 5-3 presents the benchmark regression results for the impact of climate risk on corporate stock price crash risk. The core findings are reflected in Column (2). After controlling for a range of factors potentially influencing stock price crash risk, the coefficient for climate risk is statistically significant at the 1% level. This indicates that for each unit increase in climate risk, the probability of extreme negative returns occurring rises by an average of 0.028. Similarly, the coefficient for climate risk in column (4) is statistically significant at the 5% level, indicating that for each additional unit of climate risk, the gap between downside return volatility and upside return volatility increases by an average of 0.012. Thus, this result implies that the greater a firm's exposure to climate risk, the higher the likelihood of a future stock price crash.

It follows that the benchmark regression analysis confirms the core hypothesis H1 of this paper: heightened climate risk significantly elevates a firm's risk of stock price collapse. This effect persists after controlling for multidimensional fixed effects and a range of firm characteristics, and does not depend on specific collapse risk metrics.

5.4. Robustness and Endogeneity Tests

To ensure the reliability of the benchmark regression conclusions, potential confounding factors require systematic

treatment. This section enhances the credibility of research findings through a series of rigorous tests.

Replace the core explanatory variable. Adopt the relative indicator "Climate risk expansion terms as a proportion of total annual report vocabulary (Clrisk_rate)" as the new explanatory variable. As shown in columns (1) and (2) of Table 5-4, the coefficient for Clrisk_rate is significantly positive at the 1% level when both NCSKEW and DUVOL are used as dependent variables. This indicates that climate risk measures, whether based on absolute quantity or relative frequency, amplify the risk of stock price crashes.

Replacing the Dependent Variable. To examine whether climate risk increases the probability of a crash event occurring, a binary dummy variable CRASH was employed as the dependent variable in a Logit regression. As shown in Column (3) of Table 5-4, the coefficient for Clrisk remains significantly positive at the 1% level, indicating that climate risk substantially elevates the probability of a company experiencing a stock price crash event.

Stricter fixed effects control. Columns (4) and (5) of Table 5-4 incorporate industry \times year interaction fixed effects. This specification controls for time-varying, industry-specific unobserved factors. Results show Clrisk's coefficient remains robustly positive at the 1% significance level.

Table 5-4. Robustness test: replacing core variables and strengthening fixed effects

	(1)	(2)	(3)	(4)	(5)
	NCSKEW	DUVOL	CRASH	NCSKEW	DUVOL
Clrisk			0.015*** (0.003)	0.028*** (0.007)	0.015*** (0.005)
Clrisk_rate	0.205*** (0.041)	0.082*** (0.029)			
lag_ROA	-0.094 (0.067)	-0.063 (0.045)	-0.035 (0.030)	-0.117* (0.068)	-0.071 (0.046)
lag_Growth	0.014* (0.008)	0.003 (0.006)	0.003 (0.004)	0.014 (0.009)	0.003 (0.006)
lag_Size	0.034*** (0.007)	0.015*** (0.005)	-0.003 (0.003)	0.039*** (0.008)	0.017*** (0.005)
lag_TobinQ	0.066*** (0.004)	0.041*** (0.003)	0.010*** (0.002)	0.069*** (0.004)	0.043*** (0.003)
lag_annual_return	0.061*** (0.011)	0.014* (0.007)	-0.016*** (0.005)	0.052*** (0.011)	0.008 (0.008)
lag_volatility	-0.002*** (0.000)	-0.001*** (0.000)	-0.000*** (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
lag_cash	-0.079 (0.056)	-0.059 (0.038)	-0.015 (0.024)	-0.056 (0.057)	-0.044 (0.038)
_cons	-1.138*** (0.161)	-0.571*** (0.108)	0.109 (0.067)	-1.352*** (0.166)	-0.677*** (0.111)
Firm_FE	Yes	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes	Yes
Industry_FE \times Year_FE	No	No	No	Yes	Yes
N	47562	47562	47562	47562	47562
r2_a	0.080	0.086	0.036	0.089	0.095
F	42.573	31.433	14.318	41.078	31.963

Propensity Score Matching (PSM). Using the median Clrisk value as a threshold, a treatment group (high risk) and a control group (low risk) were constructed. A series of firm

characteristics (i.e., all control variables in the model) were employed as matching covariates for 1:1 nearest neighbour matching. Regression was re-run on the matched sample.

Columns (1) and (2) in Table 5-5 show that the coefficient for Clrisk remains significantly positive. This indicates that after controlling for observable systematic differences, the impact of climate risk on stock price crashes persists.

Exclusion of the COVID-19 pandemic shock. The global COVID-19 pandemic beginning in 2020 inflicted substantial disruption on global supply chains and capital markets, potentially obscuring the true impact of climate risk. To

address this, data from 2020 onwards was excluded, with regression conducted solely on the pre-pandemic sample. As shown in columns (3) and (4) of Table 5-5, within the pre-pandemic sample, Clrisk's coefficient not only remains significantly positive but exhibits an even greater absolute value. This indicates that the findings of this paper are not driven by the external shock of the pandemic as a special period.

Table 5-5. Robustness Test: overcoming sample self-selection and excluding external shocks

	(1)	(2)	(3)	(4)
	NCSKEW	DUVOL	NCSKEW	DUVOL
Clrisk	0.025*** (0.008)	0.009* (0.005)	0.034*** (0.009)	0.018*** (0.006)
lag_ROA	-0.085 (0.074)	-0.056 (0.048)	-0.232** (0.095)	-0.169*** (0.063)
lag_Growth	0.013 (0.009)	0.003 (0.006)	0.007 (0.011)	-0.002 (0.007)
lag_Size	0.033*** (0.008)	0.014*** (0.005)	0.092*** (0.011)	0.057*** (0.007)
lag_TobinQ	0.070*** (0.005)	0.043*** (0.003)	0.082*** (0.006)	0.053*** (0.004)
lag_annual_return	0.061*** (0.012)	0.013 (0.008)	0.140*** (0.015)	0.074*** (0.010)
lag_volatility	-0.002*** (0.000)	-0.001*** (0.000)	-0.003*** (0.000)	-0.002*** (0.000)
lag_cash	-0.022 (0.061)	-0.022 (0.040)	-0.080 (0.070)	-0.046 (0.048)
_cons	-1.222*** (0.174)	-0.582*** (0.115)	-2.516*** (0.238)	-1.553*** (0.155)
Firm_FE	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes
N	42550	42550	26484	26484
r2_a	0.078	0.082	0.116	0.116
F	33.931	24.307	42.800	35.105

Table 5-6. Endogeneity test

	(1)	(2)
	Clrisk	NCSKEW
Clrisk		0.052*** (0.004)
IV_scfpeer	0.373*** (0.021)	
lag_ROA	0.102** (0.046)	-0.042 (0.054)
lag_Growth	0.006 (0.006)	0.016** (0.008)
lag_Size	0.189*** (0.006)	-0.007*** (0.003)
lag_TobinQ	-0.010*** (0.003)	0.051*** (0.003)
lag_annual_return	-0.007 (0.007)	0.054*** (0.011)
lag_volatility	0.000 (0.000)	-0.003*** (0.000)
lag_cash	0.044 (0.040)	-0.027 (0.050)
_cons	-1.526*** (0.156)	-0.126* (0.068)
Firm_FE	Yes	Yes
Year_FE	Yes	Yes
N	47562	47562
F-value of the first stage	201.786	

The instrumental variables (IV) approach addresses core endogeneity. The average climate risk exposure of peer

companies within the same industry and year (IV_scfpeer) is selected as the instrumental variable for the core explanatory variable Clrisk. Table 5-6 reports the regression results from the two-stage least squares (2SLS) method. Column (1) indicates that the coefficient for the instrumental variable IV_scfpeer is 0.373, highly significant at the 1% level. The F-statistic for the first stage reaches 201.786, far exceeding the empirical rule threshold of 10. This robustly rejects the null hypothesis of 'weak instrumentality,' confirming the strong correlation between the instrumental variable and the endogenous explanatory variable. Column (2) reveals that following instrumental variable treatment, the coefficient for Clrisk stands at 0.052, remaining significantly positive at the 1% level. Notably, this coefficient exceeds that from the benchmark OLS regression (0.028), suggesting OLS estimates may understate the true impact of climate risk due to measurement error or reverse causality.

In summary, having undergone a series of rigorous tests concerning variable measurement, model specification, sample selection bias, external shocks, and core endogeneity issues, the core conclusion of this paper—that climate risk significantly amplifies the risk of corporate share price collapse—demonstrates a high degree of robustness and reliability.

5.5. Heterogeneity Analysis

The benchmark regression analysis presented earlier confirms the pervasive impact of climate risk on corporate stock crash risk. However, this influence may not be uniform

across firms with differing characteristics.

First, we examine the moderating role of corporate governance, using CEO duality (whether the Chairman and CEO are held by the same individual) as a proxy variable. The regression results in Table 5-7 show that, in the duality sample, Clrisk coefficients are positive but not statistically significant. Conversely, in the non-duality sample, Clrisk coefficients are positively significant at the 1% level, with absolute values exceeding those in the duality sample. This finding suggests that in firms with more robust governance structures and

clearer separation of powers, both the market and the board hold management to higher expectations regarding climate risk management. Should such firms be exposed to climate risks without effective mitigation, investors may perceive this as a more severe signal of mismanagement, triggering stronger negative market reactions and thereby amplifying collapse risk. In other words, higher governance standards may be accompanied by lower tolerance for risk management failures.

Table 5-7. Heterogeneity Analysis: Based on the CEO duality

	(1)	(2)	(3)	(4)
	CEO Duality		Non-CEO Duality	
	NCSKEW	DUVOL	NCSKEW	DUVOL
Clrisk	0.023	0.010	0.035 ^{***}	0.018 ^{***}
	(0.019)	(0.013)	(0.009)	(0.006)
lag_ROA	0.076	0.076	-0.137 [*]	-0.100 [*]
	(0.143)	(0.094)	(0.077)	(0.052)
lag_Growth	-0.016	-0.022 [*]	0.017 [*]	0.007
	(0.019)	(0.013)	(0.009)	(0.006)
lag_Size	0.052 ^{***}	0.023 [*]	0.030 ^{***}	0.014 ^{**}
	(0.018)	(0.012)	(0.009)	(0.006)
lag_TobinQ	0.083 ^{***}	0.049 ^{***}	0.062 ^{***}	0.041 ^{***}
	(0.008)	(0.006)	(0.005)	(0.003)
lag_annual_return	0.025	-0.001	0.072 ^{***}	0.019 ^{**}
	(0.023)	(0.015)	(0.013)	(0.009)
lag_volatility	-0.001 ^{**}	-0.001 ^{**}	-0.002 ^{***}	-0.001 ^{***}
	(0.001)	(0.000)	(0.000)	(0.000)
lag_cash	-0.162	-0.091	-0.060	-0.049
	(0.126)	(0.083)	(0.064)	(0.043)
_cons	-1.673 ^{***}	-0.822 ^{***}	-1.160 ^{***}	-0.620 ^{***}
	(0.398)	(0.263)	(0.189)	(0.127)
Firm_FE	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes
N	12163	12163	35399	35399
r2_a	0.087	0.084	0.083	0.092
F	12.974	10.338	27.255	22.857

Secondly, we examine the moderating effect of corporate operational characteristics by grouping firms according to capital intensity. Capital-intensive enterprises typically possess substantial fixed assets (such as factories and equipment), whose value and operational efficiency are highly dependent on stable physical environments. Consequently, such firms exhibit greater sensitivity to the physical risks of climate change, including extreme weather events. Simultaneously, many capital-intensive sectors—such as heavy industry and energy—are also high-carbon emitters, facing more severe policy, technological, and market

transition risks. Based on this, we anticipate that the impact of climate risk on stock price crashes will be more pronounced in enterprises with high capital intensity. The results in Table 5-8 provide strong support for this hypothesis. Within the low capital-intensity sample, the coefficient for Clrisk is non-significant. Conversely, in the high capital-intensity sample, Clrisk coefficients are consistently positive and significant at the 1% level. This clearly indicates that the adverse impact of climate risk is concentrated among enterprises possessing substantial physical assets whose value and operations are highly exposed to climate-related hazards.

Table 5-8. Heterogeneity Analysis: Based on Capital Intensity

	(1)	(2)	(3)	(4)
	Low capital intensity		High capital intensity	
	NCSKEW	DUVOL	NCSKEW	DUVOL
Clrisk	0.018	0.004	0.040***	0.021***
	(0.012)	(0.008)	(0.010)	(0.007)
lag_ROA	0.032	0.033	-0.221**	-0.148**
	(0.096)	(0.064)	(0.100)	(0.065)
lag_Growth	0.000	-0.003	0.017	0.007
	(0.015)	(0.010)	(0.011)	(0.007)
lag_Size	0.061***	0.031***	0.029***	0.016**
	(0.013)	(0.008)	(0.010)	(0.007)
lag_TobinQ	0.071***	0.045***	0.068***	0.044***
	(0.006)	(0.004)	(0.006)	(0.004)
lag_annual_return	0.072***	0.020*	0.059***	0.019*
	(0.016)	(0.011)	(0.016)	(0.011)
lag_volatility	-0.002***	-0.001***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
lag_cash	-0.131	-0.102*	-0.027	-0.016
	(0.089)	(0.060)	(0.077)	(0.050)
_cons	-1.774***	-0.928***	-1.193***	-0.681***
	(0.274)	(0.183)	(0.237)	(0.158)
Firm_FE	Yes	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes	Yes
N	23339	23339	23352	23352
r2_a	0.081	0.089	0.083	0.085
F	22.145	17.299	18.182	16.236

In summary, the heterogeneity analysis reveals the boundary conditions under which climate risks impact stock price collapses: this negative effect is not uniform, but manifests most pronouncedly in enterprises with higher corporate governance standards and greater capital intensity.

5.6. Mechanism Testing: Mediating Effects of Supply Chain Resilience

This section employs the proportion of procurement from core suppliers (supplier concentration) as a proxy variable for supply chain resilience in regression analysis, with results presented in Table 5-9. Column (1) reports regression results for the impact of climate risk on corporate supply chain resilience. Findings indicate that the coefficient for Clrisk is -0.563, significantly negative at the 1% level. This signifies that for each unit increase in climate risk faced by an enterprise, its supply chain resilience decreases significantly by 0.563 units. This demonstrates that enterprises confronting higher climate risks exhibit markedly diminished supply chain resilience.

From a corporate behaviour perspective, when confronting highly uncertain external shocks such as climate risk, management tends to adopt defensive strategies like supplier diversification. Whilst this approach mitigates supply disruption risks in the short term, the long-term absence of strong connections at critical nodes may diminish the overall adaptability and resilience of the supply chain, thereby undermining its relational resilience.

Table 5-9. Mechanism Test

	(1)	(2)	(3)
	supplier_ratio	NCSKEW	DUVOL
supplier_ratio		-0.001*	-0.001*
		(0.000)	(0.000)
Clrisk	-0.563***	0.018*	0.008
	(0.132)	(0.010)	(0.007)
lag_ROA	3.548***	-0.096	-0.058
	(1.012)	(0.078)	(0.054)
lag_Growth	-0.090	0.013	0.003
	(0.131)	(0.010)	(0.007)
lag_Size	-2.066***	0.038***	0.017***
	(0.122)	(0.009)	(0.006)
lag_TobinQ	0.080	0.072***	0.048***
	(0.064)	(0.005)	(0.003)
lag_annual_return	0.171	0.059***	0.016*
	(0.170)	(0.012)	(0.009)
lag_volatility	-0.008**	-0.002***	-0.001***
	(0.004)	(0.000)	(0.000)
lag_cash	-2.402***	-0.095	-0.081*
	(0.899)	(0.068)	(0.047)
_cons	67.343***	-1.277***	-0.650***
	(2.682)	(0.203)	(0.141)
Firm_FE	Yes	Yes	Yes
Year_FE	Yes	Yes	Yes
N	38073	38073	38073
r2_a	0.676	0.073	0.077
F	53.007	31.088	23.238

Furthermore, the weakening of supply chain resilience (i.e., declining supplier concentration) heightens the risk of share

price collapses. Columns (2) and (3) incorporate both climate risk and supply chain resilience into the regression model for stock price crash risk. The coefficient for *supplier_ratio* was -0.001 in both models and remained significantly negative at the 10% level. This indicates that, after controlling for other factors, stronger supply chain resilience is significantly associated with lower stock price crash risk. Following the inclusion of the mediating variable *supplier_ratio*, the coefficient for the core explanatory variable *Clrisk* remained positive but decreased in magnitude and significance.

This can be explained primarily from two perspectives. Firstly, from an information asymmetry standpoint, diminished supply chain resilience leads to unstable supply and inconsistent raw material quality. These critical non-financial insights remain embedded within the supply chain network, often concealed or disclosed with delay, preventing external investors from accessing them promptly and accurately. Concurrently, management may seek to obscure such adverse operational conditions. The persistent accumulation of negative information consequently heightens the risk of collapse. Secondly, from a corporate fundamentals perspective, diminished supply chain resilience exposes firms to the cumulative impact of operational fluctuations among numerous small and medium-sized suppliers. This creates inconsistencies in response, mismatches in capabilities, and asynchronous recovery, amplifying the negative effects of production disruptions or cost escalations. Consequently, operational volatility reduces corporate profitability and cash flow stability. Investors then develop pessimistic expectations regarding future cash flows, heightening stock price sensitivity to negative news and triggering crash risks.

Synthesising the above findings, we conclude that supply chain resilience mediates partially between climate risk and stock market crash risk, thereby validating Hypothesis H2. The complete transmission pathway is as follows: rising climate risks compel enterprises to adopt defensive strategies of supplier diversification. However, this strategy erodes their original ‘relational’ supply chain resilience, further amplifying operational uncertainty and information asymmetry. Ultimately, this leads to a significant increase in the risk of stock price collapse.

5.7. Moderating Effects

This section introduces analyst attention as a moderating variable. By examining its moderating effects on direct effects and mediating pathways, we explore how external constraints influence risk transmission mechanisms. The proxy variable, ‘number of analysts (teams) tracking a company within one year’, is log-transformed after adding one. This ensures companies with no analyst coverage can undergo logarithmic transformation, preventing sample loss. It also renders the variable distribution closer to normal, mitigating heteroskedasticity, and reflects diminishing marginal returns in analyst attention.

As shown in Table 5-10, the moderating effect was tested via interaction terms. Results indicate that the moderating role of analyst coverage varies depending on the measure of stock price crash risk: in the NCSKEW model (Column 1), the interaction coefficient is 0.001 and non-significant, suggesting analyst coverage does not significantly moderate the impact of climate risk on NCSKEW. In other words, regardless of analyst coverage levels, the positive impact of climate risk on stock crash risk (based on return skewness) remains largely unchanged. In the DUVOL model (Column

2), the interaction coefficient is -0.002 and significant at the 1% level, indicating that analyst coverage exerts a negative moderating effect on the relationship between climate risk and DUVOL. Specifically, a 1% increase in analyst coverage reduces the positive impact of climate risk on DUVOL by 0.002 units, suggesting that analyst coverage mitigates the stock price crash risk induced by climate risk. Analysts, acting as information intermediaries, enhance corporate transparency and external oversight by uncovering and disseminating firm information. This reduces management incentives to conceal adverse information and diminishes information asymmetry, thereby curbing excessive volatility and crash tendencies triggered by climate risk. Hypothesis H3 is thus confirmed.

Table 5-10. Regulatory Effect: Analyst Attention

	(1)	(2)
	NCSKEW	DUVOL
<i>Clrisk</i>	0.023***	0.014**
	(0.008)	(0.006)
<i>Clrisk*lnAnaAttention</i>	0.001	-0.002***
	(0.001)	(0.001)
<i>lag_ROA</i>	-0.121*	-0.034
	(0.069)	(0.047)
<i>lag_Growth</i>	0.003	-0.003
	(0.009)	(0.006)
<i>lag_Size</i>	0.058***	0.037***
	(0.008)	(0.005)
<i>lag_TobinQ</i>	0.066***	0.043***
	(0.004)	(0.003)
<i>lag_annual_return</i>	0.056***	0.018**
	(0.012)	(0.008)
<i>lag_volatility</i>	-0.001***	-0.001***
	(0.000)	(0.000)
<i>lag_cash</i>	-0.070	-0.064
	(0.059)	(0.040)
<i>_cons</i>	-1.757***	-1.109***
	(0.178)	(0.120)
<i>Firm_FE</i>	Yes	Yes
<i>Year_FE</i>	Yes	Yes
<i>N</i>	41581	41581
<i>r2_a</i>	0.078	0.080
<i>F</i>	33.535	26.403

6. Conclusion

This study examines the impact of corporate-level climate risks on stock price crash risk among Chinese A-share listed companies from 2006 to 2024. It draws upon theories of information asymmetry, principal-agent relationships, and risk transmission. By constructing a mediated transmission model “climate risk → supply chain resilience → stock price crash risk” and introducing analyst attention as a moderating variable, this study employs panel data regression and a series of tests to reveal a dual mechanism through which climate risk influences stock price crash risk. The core findings are as follows: Firstly, corporate climate risk exhibits a significant positive correlation with stock price crash risk, indicating that firms with greater climate risk exposure face heightened prospects of future stock price collapses. This core finding demonstrates robust stability and reliability following

rigorous and comprehensive tests addressing variable measurement methods, model specification forms, sample selection biases, external shock influences, and core endogeneity issues. Concurrently, the negative effects induced by climate risk exhibit significant heterogeneity, manifesting more pronouncedly in firms with higher corporate governance standards and greater capital intensity. Secondly, supply chain resilience partially mediates the relationship between corporate climate risk and stock price crash risk. Rising climate risk undermines firms' 'relational' supply chain resilience, specifically through a decline in the procurement share of core suppliers, thereby significantly increasing stock price crash risk. Finally, analyst coverage mitigates the stock price crash risk stemming from climate risk. Higher analyst coverage weakens the indirect effect whereby corporate climate risk exacerbates stock price crash risk by reducing supply chain resilience.

Based on the above conclusions, the following policy recommendations are proposed for enterprises, investors, financial institutions, and regulatory bodies.

Enterprises should integrate climate risk management into the core of their strategic planning. Establish dedicated climate risk assessment teams and formulate corresponding contingency plans. Invest in climate-resilient infrastructure, such as data centres employing liquid cooling technology to withstand extreme heat, and power grid companies developing distributed energy systems to mitigate wildfire risks. Businesses should optimise supply chain management by prioritising deep collaborative relationships with key partners, constructing supply networks that balance flexibility with resilience. Climate risk factors can be deeply integrated into the development of 'digital-intelligent supply chains' to achieve resource sharing, risk pooling, and efficient information flow. Companies should strengthen the oversight functions of boards of directors and supervisors to ensure management fully considers shareholder interests in climate risk management decisions. Enhance disclosure quality by proactively reporting how climate risks impact supply chains, financial health, and future operations.

Investors and financial institutions must incorporate corporate climate and supply chain risks into investment valuations, developing integrated assessment tools to make more rational investment decisions. Analyst research reports should be prioritised to understand corporate climate risk management practices and analysts' projections for share prices. Financial institutions must expedite the refinement of climate risk stress testing mechanisms, incorporating climate scenarios such as supply chain disruptions caused by extreme weather to assess potential cascading effects and losses. Consideration should be given to integrating climate risk management and supply chain resilience levels into credit approval processes, while accelerating the development of climate risk hedging instruments.

Regulators should establish a comprehensive climate risk regulatory framework, collaborating with meteorological and ecological authorities to create a climate risk monitoring system. Differentiated management approaches should be applied to companies based on varying levels of analyst scrutiny. Mandatory disclosure of detailed climate risk information should be phased in by sector to enhance market transparency. Regulatory bodies must enact legislation to elevate corporate governance standards, strengthen oversight of the analyst industry, and encourage analysts to focus on non-financial factors like corporate climate risk. This will

ensure investors receive more comprehensive and accurate research reports.

References

- [1] Albuquerque R, Koskinen Y, Yang S, et al. Resiliency of Environmental and Social Stocks: An Analysis of the Exogenous COVID-19 Market Crash [J]. *The Review of Corporate Finance Studies*, 2020, 9(3): 593-621.
- [2] Ali I, Arslan A, Tarba S, et al. Supply chain resilience to climate change inflicted extreme events in agri-food industry: The role of social capital and network complexity [J]. *International Journal of Production Economics*, 2023, 264: 108968.
- [3] Bose S, Lim E K, Minnick K, et al. Does Carbon Risk Influence Stock Price Crash Risk? International Evidence [J]. *Journal of Business Finance & Accounting*, 2025, 52(5): 2111-2144.
- [4] Carvalho V M, Nirei M, Saito Y U, et al. Supply Chain Disruptions: Evidence from the Great East Japan Earthquake [J]. *The Quarterly Journal of Economics*, 2021, 136(2): 1255-1321.
- [5] Chen Z L, Li Z, Chen W. Does climate policy uncertainty affect Chinese stock market volatility? [J]. *International Review of Economics and Finance*, 2023, 84:369-381.
- [6] Christopher M, Peck H. Building the Resilient Supply Chain [J]. *International Journal of Logistics Management*, 2004, 15(2): 1-13.
- [7] Colicchia C, Strozzi F. Supply chain risk management: a new methodology for a systematic literature review [J]. *Supply Chain Management: An International Journal*, 2012, 17(4): 403-418.
- [8] Cuculiza C, Kumar A, Xin W, et al. Temperature sensitivity, mispricing, and predictable returns [J]. *Management Science*, 2025.
- [9] Francesca D, Barbara A, Matthias K, et al. Climate actions and macro-financial stability: The role of central banks [J]. *Journal of Environmental Economics and Management*, 2021, 110:102548.
- [10] Gan K, Li R, Zhou Q. Climate transition risk, environmental news coverage, and stock price crash risk [J]. *International Review of Financial Analysis*, 2024, 96: 103657.
- [11] Giglio S, Kelly B, Stroebel J. Climate finance [J]. *Annual review of financial economics*, 2021, 13(1): 15-36.
- [12] Guo K, Ji Q, Zhang D. A dataset to measure global climate physical risk [J]. *Data in Brief*, 2024, 54:110502.
- [13] Guo X, Li R. Climate physical risks and corporate supply chain resilience: How do investor sentiment and risk-taking behaviors influence supply chain operations? [J]. *Finance Research Letters*, 2025, 85: 107903.
- [14] Huynh T D, Xia Y. Climate change news risk and corporate bond returns [J]. *Journal of Financial and Quantitative Analysis*, 2021, 56(6): 1985-2009.
- [15] Inoue H, Todo Y. Firm-level propagation of shocks through supply-chain networks [J]. *Nature Sustainability*, 2019, 2(9): 841-847.
- [16] Intergovernmental Panel on Climate Change. Climate change 2022: impacts, adaptation and vulnerability: summary for policymakers [R/OL]. 2022. <https://www.ipcc.ch/report/ar6/wg2/>.
- [17] Jia L, Li J. How does digital collaboration impact supply chain resilience [J]. *Finance Research Letters*, 2024, 66:105684.
- [18] Jin L, Myers C S. R 2 around the world: New theory and new tests [J]. *Journal of Financial Economics*, 2004, 79(2): 257-292.

- [19] Krueger P. The Importance of Climate Risks for Institutional Investors [J]. *The Review of Financial Studies*, 2020, 33(3): 1067-1111.
- [20] Li J, Zhou Z Q, Zhang Y, et al. Information interaction among institutional investors and stock price crash risk based on multiplex networks [J]. *International Review of Financial Analysis*, 2023, 89: 102780.
- [21] Li Q, Shan H Y, Tang Y H, et al. Corporate climate risk: measurements and responses [J]. *The Review of Financial Studies*, 2024, 37(6): 1778-1830.
- [22] Lin B, Wu N. Climate risk disclosure and stock price crash risk: The case of China [J]. *International Review of Economics & Finance*, 2023, 83: 21-34.
- [23] Magnan A K, Portner H O, Duvat V K E, et al. Estimating the global risk of anthropogenic climate change [J]. *Nature Climate Change*, 2021, 11: 879-885.
- [24] Naseer M M, Guo Y, Bagh T, et al. Sustainable investments in volatile times: Nexus of climate change risk, ESG practices, and market volatility [J]. *International Review of Financial Analysis*, 2024, 95: 103492.
- [25] Ni X, Si Y, Zhang B. Climate Vulnerability and Stock Price Crash Risk Worldwide [J]. *SSRN Electronic Journal*, 2022: 3930554.
- [26] Pankratz N M C, Schiller C M. Climate change and adaptation in global supply-chain networks [J]. *The Review of Financial Studies*, 2024, 37(6): 1729-1777.
- [27] Swiss Re Institute. Economics of climate change: no action not an option [R/OL]. 2021-04-22. <https://www.swissre.com/institute/research/topics-and-risk-dialogues/climate-and-natural-catastrophe-risk/expertise-publication-economics-of-climate-change.html>.
- [28] Wu N Q, Xiao W G, Liu W, et al. Corporate climate risk and stock market reaction to performance briefings in China [J]. *Environmental science and pollution research international*, 2022, 29(35): 53801-53820.
- [29] Xu X, An H, Huang S, et al. Measurement of daily climate physical risks and climate transition risks faced by China's energy sector stocks [J]. *International Review of Economics and Finance*, 2024, 93: 625-640.
- [30] Ye Y, Zhu J, Li B, et al. Extreme climate risks and corporate bond yield spreads: evidence from China [J]. *Asia-Pacific Journal of Accounting & Economics*, 2024, 31(5): 697-717.
- [31] Zhang L, Fan H, Zhang J, et al. Climate Risk and Stock Price Crash: The Role of Text-Based Carbon Disclosure [J]. *Accounting & Finance*, 2025, 65(3): 3107-3141.
- [32] Zhang P, Deschenes O, Meng K, et al. Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants [J]. *Journal of Environmental Economics and Management*, 2018, 88: 1-17.