
*Research article***Industry climate risk, production networks and firm ESG performance****Junfan Ren¹, Taofeng Chen^{2,*} and Zhihao Hu³**¹ School of Economics, Lanzhou University of Finance and Economics, Lanzhou, China² School of Economics and Management, Ningbo University of Technology, Ningbo, China³ Institute of Finance & Banking, Chinese Academy of Social Sciences, Beijing, China*** Correspondence:** Email: taofeng_chen@sina.com, chentaofoeng@nbut.edu.cn.

Abstract: Climate change exposes firms to increasing climate-related risks; however, researchers have largely overlooked how these risks transmit through production networks to affect firm sustainability. To address this gap, we integrated industry climate risk, production networks, and firm ESG performance into a unified analytical framework. Using data from A-share listed companies in Shanghai and Shenzhen between 2009 and 2022, we empirically examined the direct effects and network spillover effects of industry climate risk on firm ESG performance. The findings revealed that industry climate risk not only exerts a direct negative effect on firm ESG performance but also generates significant spillover effects through production networks, with upstream spillovers originating from the supply side being particularly pronounced. This impact exhibits heterogeneity: It is more significant for large-scale firms, non-state-owned enterprises, and during periods of unbalanced production network structure. Moreover, high-carbon industries are primarily affected by network spillover effects, while low-carbon industries are more subject to direct effects. Mechanism analysis indicated that industry climate risk undermines firm ESG performance mainly by inhibiting green innovation, tightening financing constraints, and elevating systemic asset risk, with production networks further amplifying these transmission mechanisms. Further analysis showed that the environmental dimension is more sensitive to direct effects, whereas the social dimension responds more strongly to network effects. Notably, while upstream firms experience negative network spillovers, their direct effects are significantly positive. In contrast, downstream firms face dual suppression from direct and network effects. Moreover, higher investment efficiency can effectively mitigate the negative impact of climate risk. This study contributes to the literature by uncovering the production network transmission mechanism of climate risk and provides novel evidence on the heterogeneous effects across supply chain positions. The findings inform policymakers on designing networked and differentiated governance strategies to enhance firm ESG resilience in the face of climate change.

Keywords: climate risk; production networks; direct effects; network spillover effects; ESG performance

JEL Codes: Q54, D57, G30

1. Introduction

In recent years, extreme weather events triggered by global climate change have occurred with increasing frequency, their impact reaching far greater depth and breadth than anticipated. According to a report by Germanwatch, from 1995 to 2024, over 9700 extreme weather events worldwide resulted in more than 832000 fatalities and directly caused nearly 4.5 trillion US dollars in economic losses. China is particularly sensitive to and significantly impacted by global climate change. CMA Climate Change Centre (2024) indicates that from 1961 to 2023, China's annual average surface temperature showed a significant upward trend, increasing by 0.3 °C per decade, which is higher than the global average warming rate over the same period. Concurrently, China's average annual precipitation also displayed an increasing trend, rising by 5.2 millimeters per decade, with the frequency of extreme heavy precipitation events continually increasing. Such climate risks pose severe challenges to China's economic development and the sustainable operations of its firms. In response, the report of the 20th National Congress of the Communist Party of China pointed out the need to "promote the building of a Beautiful China and plan development from the perspective of harmonious coexistence between man and nature." Furthermore, with the continuous deepening of the top-level design for China's "Dual Carbon" goals (carbon peaking and carbon neutrality), investor attention to the ESG (Environment, Social, Governance) concept has rapidly increased. Against this backdrop, how firms manage climate risks to foster sustainable competitiveness has become a critical survival issue.

Climate risk poses a systemic threat to the very foundations of the industrial economy. When climate risks accumulate and manifest in specific industries, they form heterogeneous "industry-specific climate risks." This refers to the distinct differences in risk exposure and transition costs faced by industries due to their inherent disparities in physical exposure (e.g., floods and droughts) and transition pressures (e.g., carbon pricing, and low-carbon transition). Such industry-level climate risks can further propagate downward, not only directly disrupting day-to-day operations within firms, but also potentially transforming the very foundation of their sustainable development; their ESG performance. As a key driver of firm sustainability, superior ESG performance is not only regarded as an effective means to enhance organizational resilience (Chen and Li, 2024) and alleviate financing constraints (Yao and Zhang, 2025) but also serves as a core driver for green innovation (Huang et al., 2025). Therefore, clarifying how industry-specific climate risk affects firm ESG performance has become a critical and urgent proposition.

However, the mechanisms through which industry-specific climate risk impacts firm ESG performance are far more complex than they appear on the surface. Existing analyses often treat firms as isolated entities, neglecting the crucial role of production networks formed by modern input-output linkages (Acemoglu et al., 2016). Within these networks, an industry's inherent climate risk is not confined; it transmits structurally as price signals and responsibility pressures upstream and downstream. This suggests that a firm's final ESG performance is not only a response to the climate risk within its own industry but also an adaptive adjustment to the overall climate risk posture of the

production network in which it is embedded. This indirect, structural impact based on production network linkages may be more profound and extensive than direct shock.

Unfortunately, researchers have failed to adequately integrate the logical chain of “industry-specific climate risk – production network – firm ESG performance.” On one hand, while a few researchers focus on the direct impact of external climate risk on firm ESG performance (Zhou et al., 2024), they overlook the heterogeneous characteristics of climate risk when aggregated at the industry level and its transmission pathways through production networks. On the other hand, although some researchers examine the diffusion of micro-level shocks through production networks (Acemoglu et al., 2012, 2016; Baqaee and Farhi, 2020; Baqaee and Rubbo, 2023) or explore the influence of network position on firm ESG performance (Hu et al., 2025), few studies systematically reveal how industry-specific climate risk affects firm ESG performance through specific production network linkages. Critically, while Li et al. (2025) examined the industry-level transmission of climate risk within business groups, and Chen et al. (2024) analyzed the network diffusion effects of financial uncertainty shocks, neither study extends its analytical endpoint to the realm of firm green performance. The former concentrates on the procedural mechanisms of risk transmission itself, whereas the latter focuses on the volatility spillover of financial variables; in both cases, firm ESG performance is not incorporated as a core outcome variable of interest. This fragmentation in research perspectives and the resultant misalignment in analytical endpoints obscure the true transmission trajectory of climate risk within the economy and its ultimate implications for firm sustainable development. Consequently, it constrains the formulation of targeted policies aimed at bolstering industrial chain resilience and advancing firm ESG performance.

To address this, we aim to systematically investigate the impact of industry-specific climate risk on firm ESG performance from the perspective of production network linkages. Building on the identification of the direct shock effect of industry climate risk on firm ESG performance, Chinese multi-industry input-output data are further incorporated to construct a production network spillover effect indicator. This enables us to empirically examine how industry climate risk generates network spillover effects through upstream and downstream linkages and to delve into the underlying mechanisms. The potential marginal contributions of this paper are as follows: Theoretically integrating heterogeneous industry-specific climate risk, production networks, and firm ESG performance into a unified analytical framework, examining new mechanisms through which climate risk affects firm sustainable behavior from a network spillover perspective; methodologically integrating industry-level climate risk measurement, input-output matrices, and micro-level firm ESG data by constructing an inter-industry climate risk network spillover indicator, providing a feasible operational paradigm for identifying the micro-level effects of climate risk from the perspective of input-output linkages; and policy-wise, offering insights for collaborative climate risk management and integrated corporate ESG strategy formulation.

2. Literature review

2.1. *The impact of climate risk on firms*

The impact of climate risk on firm operational performance and value cannot be underestimated. Extreme weather events that induce climate risks cannot only directly lead to damage to infrastructure and production equipment, driving up firm operating costs, but may also cause transportation disruptions and supply chain interruptions, thereby worsening the sales environment for firms (Huang

et al., 2018; Berkman et al., 2024). These physical risks directly erode firm profits and asset bases. The deeper impact is reflected at the level of firm financing and valuation. By altering the risk perceptions of investors and creditors, climate risk reshapes the pricing logic of capital markets. Krueger et al. (2020) provided foundational evidence for this mechanism through a global survey of institutional investors, revealing that investors generally believe climate risks, particularly regulatory risks, have begun to materialize and carry financial implications for portfolio firms. Notably, long-term, large, and ESG-oriented investors are more inclined to address climate risks through risk management and engagement rather than divestment, indicating that investor responses to climate risk are strategic and heterogeneous. This shift in risk perception directly translates into financing consequences: climate risk exacerbates firms' debt and equity financing costs (Cepni et al., 2024), as markets demand higher risk premiums to compensate for potential uncertainties. Ilhan et al. (2023) extended this line of inquiry by demonstrating that institutional investors not only perceive climate risks but also actively demand climate risk disclosures. Their survey and empirical analyses of holdings data show a significantly positive association between climate-conscious institutional ownership and better firm-level climate risk disclosure. This suggests that investors exert governance pressure on firms through disclosure requirements, forming an additional transmission channel through which climate risk affects firm value. Furthermore, with the trend toward a low-carbon economic transition, transition risks arising from policy changes (e.g., carbon taxes) and technological innovations (e.g., clean energy substitution) may accelerate the depreciation of high-carbon assets. The combined effect of physical and transition risks leads to a decline in firm market value through two channels: rising discount rates and reduced expectations for future cash flows (Berkman et al., 2024; Zhang et al., 2023; Addoum et al., 2020).

Furthermore, the impact of climate risks on firm value is not confined to direct gains and losses within valuation models. With the growing prominence of ESG investment principles, climate risks are triggering more severe value repricing by systematically and multidimensionally eroding a firm's ESG foundations. At the environmental level (E), physical risks such as extreme weather can directly destroy environmental facilities, cause pollution incidents, and derail emission reduction targets while amplifying environmental risks through supply chain transmission (Hall et al., 2023). In the social dimension (S), climate risk may prompt firm management to reduce investments in ESG projects and green innovation initiatives, thereby lowering performance in firm social responsibility (Chen et al., 2023). In the governance dimension (G), uncertainties such as climate risk exposure can lead to firm financial distress. Major shareholders often provide financial support through related-party transactions. However, due to the opacity and complexity of such transactions, major shareholders may not effectively fulfill their roles, which can reduce firm governance standards (Yan et al., 2023). When a firm experiences significant negative events in any of the E, S, or G dimensions, mainstream ESG rating agencies are likely to swiftly downgrade its score, directly manifested as a decline in firm value.

2.2. Localized shocks in production networks and transmission effects

The role of production networks in transmitting and amplifying localized shocks is a key topic in economics. This strand of literature can be traced back to the work of Long and Plosser (1983), who constructed a multi-sector real business cycle model and theoretically demonstrated that microeconomic shocks can diffuse through production networks to generate aggregate economic fluctuations. Moreover, scholars have begun to further infirm intermediate goods into economic growth models to examine how micro-shocks are transmitted and amplified via input-output linkages. A seminal example is the research

by Acemoglu et al. (2012), who pioneered a Cobb-Douglas production network model and found that heterogeneous sectoral shocks can aggregate through input-output linkages, causing aggregate economic fluctuations. Building upon this, Acemoglu et al. (2016, 2017) further expanded the theory of micro-shock transmission through production networks. Based on this research framework, Zhou and Xiao (2022), Xiao and Hou (2023), Li et al. (2025), and Li et al. (2024) introduced factors such as exchange rate fluctuations, inflation, financial resource misallocation, and tax distortions into theoretical models, respectively, to explore the amplification effects of production networks on such micro-shocks.

Other researchers have relaxed specific production function forms, shifting toward constructing non-parametric theoretical models of production networks. A representative work was by Baqaee and Farhi (2020), who pointed out that Hulten's (1978) theory suffers from the flaw of ignoring the second-order effects of micro-shocks. Therefore, building upon Hulten's theory, they developed a non-parametric framework for transmitting various types of micro-shocks. The research framework of Baqaee and Farhi (2020), being open and theoretical, has gradually become a benchmark in the academic field. Based on this framework, Ni (2022a, 2022b) embedded factors such as indirect taxes and imported intermediate goods into models, quantifying the transmission effects of imposing indirect taxes on Total Factor Productivity (TFP) loss under closed and open conditions, respectively.

Researchers also focus on how localized shocks are transmitted through production networks to affect micro-firms. A typical example is the study by Chen et al. (2024), who constructed a general equilibrium model of a "production-financing" network incorporating financial uncertainty shocks. They innovatively revealed how industry-level financial uncertainty affects firm output along the upstream and downstream paths of the production network, thus providing a micro-foundation for understanding risk transmission mechanisms. More closely related to this study is the work of Li et al. (2025), where business group climate risk was the research subject. These researchers found that the climate risk of business groups also affects the cash holding ratios of subsidiaries through production network linkages, directly and via upstream and downstream connections within the network. Furthermore, other researchers have examined the impact of the COVID-19 pandemic (Miranda-Pinto et al., 2023) and natural disasters (Carvalho et al., 2021) on firm operations and output from a production network perspective. Collectively, these studies demonstrate that the production network transmission effect of shocks is a key mechanism influencing firm behavior and performance, highlighting the importance of assessing risks and policy effectiveness from a network structure perspective in the modern economy.

2.3. Summary

In summary, while the literature has separately delved into the impact of climate risk on firms and the amplification effects of production networks in transmitting localized shocks, research that integrates these two areas remains scarce. Although a few researchers have begun to focus on the transmission of climate risk along production networks (Li et al., 2025), the complete mechanism chain, starting from "industry climate risk," transmitted through "production networks," and reaching "firm ESG performance", has yet to be systematically revealed and integrated. To address this gap, we integrate industry climate risk, production networks, and firm ESG performance into a unified analytical framework. We aim to thoroughly examine, from the perspective of production network spillovers, how climate risk influences firm ESG performance through input-output linkages. By doing so, we seek to elucidate the transmission pathways and underlying mechanisms, thereby bridging the gap in the research at this interdisciplinary intersection.

3. Theoretical analysis and hypothesis development

3.1. Direct and network effects of industry climate risk on firm ESG performance

Industry climate risk refers to the systemic risk formed by the aggregation of physical and transition risks induced by climate change within an industry. The uncertainty generated by such risk within an industry systematically undermines the stable operating environment and sustainable resource base upon which firms rely to enhance their ESG performance. According to the real options theory (Pindyck, 1993; Dixit and Pindyck, 1994), when an industry is exposed to climate risk, the value of the “option to wait” for inaction becomes higher for firms within it. This leads to a widespread curtailment of strategic investments aimed at improving environmental performance, fulfilling social responsibilities, and optimizing governance structures, which is directly reflected in lower ESG performance. Therefore, industry climate risk imposes a direct negative impact on firm ESG performance. The direct consequence is the significant suppression of ESG performance levels by inhibiting investments in sustainable green innovation and distorting resource allocation oriented toward long-term value. Hence, Hypothesis H1a is proposed.

H1a: An increase in industry climate risk directly inhibits firm ESG performance.

With the deep integration of industrial and value chains, the production networks formed by inter-industry input-output linkages, while fostering technological progress (Acemoglu and Azar, 2020), have also become critical channels for the transmission of various risks. As a significant source of systemic risk, climate risk not only directly affects individual industries but also generates substantial cross-industry spillover effects through production networks, thereby impacting the ESG performance of connected firms and creating a chain reaction.

For downstream firms, they primarily face “supply-side shocks” from upstream industries. When upstream industries suffer production disruptions, cost increases, or supply shortages due to physical climate risks (e.g., extreme weather events, droughts, and sea-level rise) or climate transition risks (e.g., policy tightening, technological shifts, and market preference switching to low-carbon products), downstream firms, to maintain their own production stability, are often forced to resort to alternative suppliers with lower ESG standards and weaker environmental compliance in the short term. This compromise not only makes it difficult for downstream firms to ensure the environmental standards of raw materials but may also increase their supply chain’s carbon emissions and pollution risks, directly harming their own ESG ratings and reputation. This is particularly evident in the environmental (E) dimension and social (S) dimension related to supply chain management.

For upstream firms, they mainly face “demand-side shocks” from downstream. As downstream industries or end-markets deepen their understanding of climate risks, their procurement standards often become increasingly stringent; for example, requiring suppliers to provide carbon footprint data, adopt clean energy, disclose environmental information, or comply with certain green certifications. If upstream firms, due to insufficient technology, capital, or managerial capacity, fail to meet these green procurement requirements promptly, they may fall into a negative cycle of “order loss → financial strain → insufficient ESG investment → further decline in competitiveness.” This trap particularly hinders substantive improvements in areas such as pollution control, energy consumption reduction, employee welfare, and governance structure optimization, thereby suppressing the overall enhancement of their ESG performance. Hence, Hypothesis H1b is proposed.

H1b: Industry climate risk inhibits firm ESG performance through upstream and downstream spillover effects within production networks.

3.2. Mechanisms through which industry climate risk affects firm ESG performance

3.2.1. Green innovation

Industry climate risk suppresses firm ESG performance by crowding out or disrupting resources and activities related to green innovation through direct and indirect channels. As a core initiative for firms to achieve low-carbon transition and cope with climate pressures (Chen, 2008), the process of green innovation is highly susceptible to the resource constraints (Tan and Yan, 2021) and managerial panic (Chen et al., 2021) induced by climate risk.

First, industry climate risk directly crowds out strategic resources allocated for green innovation. On one hand, to address physical climate risks, firms are compelled to increase capital expenditures on facility maintenance, emergency measures, and post-disaster recovery. On the other hand, to cope with transition risks (e.g., policy tightening and rising technical standards), firms also face higher compliance modification and certification costs. These types of expenditures are characterized by their “rigidity” and “urgency,” directly consuming firms’ limited financial resources and management attention, leading to a substantial reduction in strategic investments originally intended for long-term, cutting-edge green technology R&D. Furthermore, according to the “Prospect Theory” in behavioral economics (Tversky and Kahneman, 1974), when rising uncertainty stems from climate risk, firm management tends to exhibit “loss aversion,” opting to allocate resources to maintaining traditional businesses that avoid short-term, certain losses, rather than investing in green innovation projects characterized by long cycles and high uncertainty.

Second, industry climate risk generates significant suppressive spillover effects on the green innovation activities of upstream and downstream firms through production network linkages. For downstream firms, “supply-side shocks” from upstream (e.g., disruption in the supply of raw materials with high green standards) force a strategic shift towards supply chain stabilization and sourcing alternatives, directly interrupting or delaying planned green product development. Concurrently, inconsistencies in environmental technology standards between old and new suppliers further disrupt the established green innovation pathways of downstream firms. For upstream firms, “demand-side shocks” (market volatility) from downstream weaken their financial foundation and deteriorate future expectations, systematically suppressing green innovation activities that require long-term investment. Hence, Hypothesis H2 is proposed.

H2: An increase in industry climate risk weakens firm green innovation through direct and production network spillover effects, thereby inhibiting firm ESG performance.

3.2.2. Financing constraints

Financing constraints constitute another key channel through which industry climate risk inhibits firm ESG performance. Climate risk significantly increases the cost and difficulty of external financing by exacerbating information asymmetry and deteriorating firm financial conditions and prospects, thereby constraining the financial capacity of firms to undertake ESG investments.

First, industry climate risk directly weakens firms' internal financing capacity and raises the threshold for external financing. Faced with shocks from physical and transition climate risks, firm profit volatility increases and cash flow stability declines, directly eroding internal capital accumulation, which is an important source of long-term ESG investment for firms. Moreover, according to financial friction theory (Bernanke and Gertler, 1995), external investors and creditors are becoming increasingly sensitive to climate risk, consequently demanding higher risk premiums or attaching more stringent collateral and covenant terms. Particularly when facing transition risks, high-carbon or slow-to-transition firms may be categorized as high-risk, leading to a sudden increase in their financing cost burden (Cepni et al., 2024).

Second, industry climate risk further intensifies the degree of financing constraints for upstream and downstream firms through production network linkages. For downstream firms, "supply-side shocks" from upstream (e.g., soaring raw material prices or supply disruptions caused by climate risk) increase their operating costs and supply chain uncertainty. Once captured by financial institutions, signals of such cost increases and supply chain vulnerability lead creditors like banks to raise credit thresholds, reduce credit lines, or demand more collateral for downstream firms, significantly increasing their external financing costs. For upstream firms, "demand-side shocks" from downstream result in reduced orders and declining operating revenue, triggering concerns among financial institutions about their debt-servicing ability and consequently tightening financing channels. Thus, industry climate risk amplifies financial distress at individual nodes through the production network, causing financing constraints to diffuse and resonate between upstream and downstream, systematically eroding the financial foundation for firm ESG investment. Hence, Hypothesis H3 is proposed.

H3: An increase in industry climate risk tightens firm financing constraints through direct and production network spillover effects, thereby inhibiting firm ESG performance.

3.2.3. Systematic asset risk

Systematic asset risk reflects the sensitivity of a firm's asset value to industry and market fluctuations (Fama and French, 1993, 2015). When industry climate risk intensifies, systematic asset risk rises significantly (Song and Fang, 2023), becoming a key financial channel for transmitting climate shocks and inhibiting firm ESG performance.

First, industry climate risk directly elevates the level of firm systematic asset risk by increasing the uncertainty of cash flows (Gu et al., 2025). Physical and transition climate risks disrupt normal business operations, leading to lower and more volatile future earnings expectations. In asset pricing models, this increase in fundamental risk is directly reflected in a stronger correlation between asset returns and market volatility, i.e., a higher systematic risk coefficient. For high-carbon or climate-exposed firms, their asset values decline during the economic low-carbon transition (Van der Ploeg and Rezai, 2020) and investors demand higher risk compensation, further amplifying the sensitivity of their asset prices to market fluctuations.

Second, industry climate risk triggers synchronized fluctuations in the asset prices of upstream and downstream firms through production network transmission, thereby systematically raising firm systematic asset risk. For downstream firms, upstream suppliers affected by climate risk may cause sharp fluctuations or disruptions in raw material prices, directly undermining downstream firms' cost control capabilities and production continuity, thereby affecting the stability of their future cash flows. Investors will accordingly reassess the risk exposure of downstream firms and may concurrently downgrade their asset valuations, leading to abnormal stock price volatility and an ensuing increase in

systematic asset risk. For upstream firms, when downstream industries face demand contraction or transition pressure due to climate risk, reduced orders and revenue declines are transmitted upstream, subjecting their asset returns to greater market volatility and thus increasing systematic asset risk. This type of “climate risk transmission” triggered by input-output linkages often manifests in financial markets as a sentiment amplification effect: Based on concerns about overall industry chain risk, investors collectively revalue assets in related sectors, triggering cross-firm, cross-tier asset price resonance, forcing firms to passively bear higher systematic risk. Hence, Hypothesis H4 is proposed.

H4: An increase in industry climate risk exacerbates firm systematic asset risk through direct and production network spillover effects, thereby inhibiting firm ESG performance.

4. Research design

4.1. Econometric model specification

To examine the direct effects and production network spillover effects of industry climate risk shocks on firm ESG performance, we establish the baseline econometric model as follows:

$$Esg_{gt} = \alpha_0 + \alpha_1 ClimateRisk_{it} + \alpha_2 Network_{it} + \alpha_3 Control_{gt} + \mu_g + \lambda_t + \varepsilon_{gt} \quad (1)$$

$$Esg_{gt} = \alpha_0 + \alpha_1 ClimateRisk_{it} + \alpha_2 Up_{it} + \alpha_3 Down_{it} + \alpha_4 Control_{gt} + \mu_g + \lambda_t + \varepsilon_{gt} \quad (2)$$

In the above equation, i , g and t denote the industry, firm, and time period, respectively; Esg_{gt} represents the ESG performance of the firm; $ClimateRisk_{it}$ is the industry-level climate risk; $Network_{it}$ refers to the aggregate spillover effect of industry climate risk transmitted through the production network; Up_{it} and $Down_{it}$ are the spillover effects of industry climate risk transmitted via upstream and downstream directions of the production network, respectively; $Control_{gt}$ denotes the set of control variables; and μ_g , λ_t and ε_{gt} represent the individual fixed effects, time fixed effects, and random disturbance term, respectively.

4.2. Variable definitions

4.2.1. Industry climate risk

To address the need for a context-specific industry climate risk measure in China’s A-share market, the approach of Du et al. (2023) is adopted. Existing indicators (Engle et al., 2020) are primarily developed for English-language earnings calls or news, which are not directly applicable due to linguistic complexity and the limited length of Chinese earnings calls. Chinese annual reports offer a more comprehensive and regulated disclosure of climate-related risks. Therefore, following Du et al. (2023), annual reports of A-share listed companies from 2009 to 2022 are first extracted from the Cninfo website. Next, a set of 98 “climate risk” keywords is identified, covering three categories: acute risk, chronic risk, and transition risk (where acute and chronic risks constitute physical risk), as detailed in Table 1. Then, the ratio of these keywords to the total word count in each annual report is calculated to construct a firm-level climate risk indicator. Finally, based on the

OECD's 2025 edition Inter-Country Input-Output (ICIO) database, firm-level climate risk is aggregated to the industry average to represent industry climate risk.

Table 1. Climate risk word set.

Risk Type	Word Set
Acute Risk	Disaster, Earthquake, Typhoon, Tsunami, Drought & Flood, Extreme, Severe, Waterlogging, Gale, Sandstorm, Hurricane, Frost, Flood, Storm, Mudslide, Landslide, Ice Jam, Snow Disaster, Drought, Flood, Rainstorm, Tornado, Hail, Flood, Rain & Snow, Freezing, Blizzard, Freezing Damage, Drought, Drought Condition, Heavy Rainfall, Flood, Severe Cold, Sandstorm
Chronic Risk	Climate, Weather, Humid, Water Temperature, Temperature Drop, Cold, Temperature, Rainfall, Temperature, Rain, Rainy Season, Rain Condition, Precipitation, Overcast Rain, Rainy, Extreme Cold, Winter, Flood Season, High Humidity, Water Regime, Water Level, Light, Water Shortage, Alpine, Cold Wave, Subsidence, Groundwater, Flood Condition, Surface, Water Storage
Transition Risk	Energy Saving, Energy, Clean, Ecology, Environment, Transition, Solar Energy, Upgrade, Recycling, Utilization Rate, Nuclear Power, Wind Power, Natural Gas, Efficiency Increase, Fuel Oil, Efficiency, Renewable, Emission Reduction, Environmental Protection, Green, Low Carbon, Energy Consumption Reduction, Fuel, Water Saving, Photovoltaic, High Efficiency, Retrofit, Fuel Consumption, Power Consumption, Energy Consumption, Wind Power, Photovoltaic, Efficiency, Intensive

To systematically capture the overall trend of climate risk in China, we calculate the annual mean of industry climate risk. The results are shown in Figure 1. The analysis indicates that from 2009 to 2022, China's industry climate risk exhibited a fluctuating upward trend. Especially after 2019, as the impacts of global warming intensified, extreme weather events in China have shown significant characteristics of becoming more frequent, more severe, and more widespread. Notable examples include the extreme spring drought in Yunnan Province in 2019 and the rare summer-autumn drought in the Yangtze River Basin in 2022. Affected by these events, industries on one hand faced increasingly severe physical climate risks, and on the other hand bore the transition risks associated with the low-carbon shift, leading to a significant rise in the average industry climate risk from 2019 to 2022.

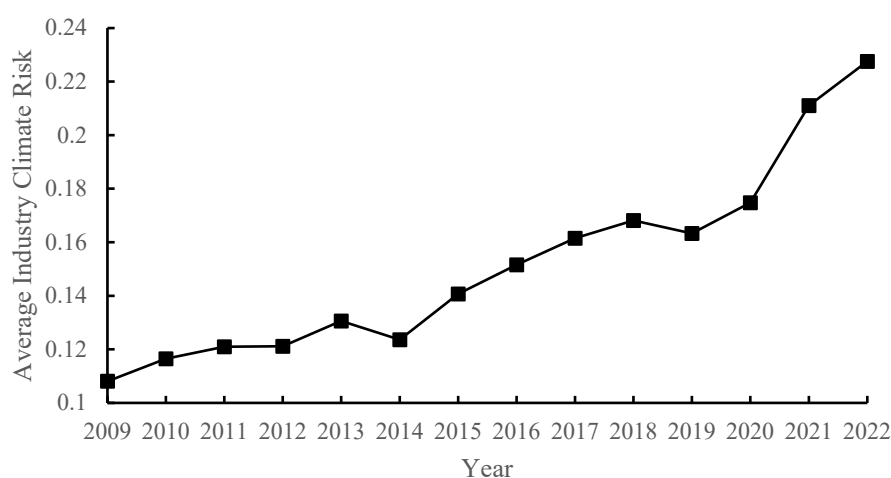


Figure 1. Overall Trend of Industry Climate Risk (2009–2022).

4.2.2. Production network spillover effects

Based on the 2025 edition (updated to 2022) of the OECD's Inter-Country Input-Output (ICIO) database, China's input-output tables for the period 2009–2022 are extracted to construct the Leontief inverse matrix. Following the methodologies of Chen et al. (2024) and Li et al. (2025), the production network spillover effect indicators are constructed. The specific construction method is as follows:

$$Up_{it} = \sum_j Input_{j \rightarrow i} \left(\frac{1}{N_g} \sum_g ClimateRisk_{igt} \times 100 \right) \quad (3)$$

$$Down_{it} = \sum_j Output_{j \rightarrow i} \left(\frac{1}{N_g} \sum_g ClimateRisk_{igt} \times 100 \right) \quad (4)$$

$$Network_{it} = Up_{it} + Down_{it} \quad (5)$$

In Equations (3)–(5), g denotes the firm, $\frac{1}{N_g} \sum_g ClimateRisk_{igt} \times 100$ represents the industry climate risk, which is derived by averaging firm-level climate risks within the industry, $\sum_j Input_{j \rightarrow i} \left(\frac{1}{N_g} \sum_g ClimateRisk_{igt} \times 100 \right)$ measures the magnitude of climate risk shock from upstream industry spilling over to downstream industry i through the production network, and $\sum_j Output_{j \rightarrow i} \left(\frac{1}{N_g} \sum_g ClimateRisk_{igt} \times 100 \right)$ captures the magnitude of climate risk shock from downstream industry spilling over to upstream industry i . $Network_{it}$ is the aggregate network spillover effect. It is important to note that, to isolate the production network spillover effect from the direct effect, the diagonal elements of the Leontief inverse matrix are set to zero.

4.2.3. Dependent variable and control variables

The dependent variable in this paper is firm ESG performance (Esg_{gt}), Shanghai Hua Zheng Index Co., Ltd. assesses firm sustainable development performance across the Environmental (E), Social (S), and Governance (G) dimensions, based on which it assigns a value and provides a corresponding score¹ for firm ESG performance. Here, we select the assigned ESG value as the dependent variable and apply a logarithmic transformation to it. Firm-level control variables include: The proportion of independent directors ($Indep_{gt}$), calculated as the number of independent directors divided by board size; capital intensity ($Capital_{gt}$), measured as total assets divided by operating revenue and taken in logarithm; the fixed asset ratio (Ppe_{gt}), computed as net fixed assets divided by total assets; firm age (Age_{gt}), defined as the difference between the current year and the firm's founding year and taken in logarithm; return on assets (Roa_{gt}), calculated as net profit divided by total assets; Tobin's Q ($Tobin_{gt}$), measured as firm market value divided by total assets; the

¹ Shanghai Hua Zheng Index Co., Ltd. assigns a value from 1 to 9 to firm ESG ratings ranging from "C" to "AAA" and also provides a standardized score ranging from 0 to 100.

shareholding ratio of the largest shareholder ($Share1_{gt}$), computed as the shares held by the largest shareholder divided by total shares outstanding; the asset-liability ratio (Lev_{gt}), defined as total liabilities divided by total assets; total factor productivity (Tfp_{gt}), estimated using the OP method (Olley and Pakes, 1996); and the nature of ownership ($State_{gt}$), which equals 1 for state-owned firms and 0 otherwise.

4.2.4. Data processing and descriptive statistics

Apart from the variables for industry climate risk, production network spillover effects, and firm ESG performance, the raw data for all other control variables are obtained from the CSMAR database. The following data preprocessing steps are applied: excluding ST, *ST, and PT firms; removing companies listed for less than one year, those that have been delisted, or whose trading is suspended; eliminating firms with significant missing values or statistical anomalies; and matching industry-level data (industry climate risk and production network spillover effects) with firm-level data according to the respective industry classifications. Ultimately, we construct a balanced panel dataset at the firm level covering the period from 2009 to 2022.

Table 2 presents the descriptive statistics of the main variables. The constructed balanced panel dataset spans 2009–2022 and contains 31479 valid observations. The sample covers nearly the vast majority of A-share listed companies in China, indicating broad representativeness. Furthermore, the variables exhibit substantial variation across statistics such as mean, maximum, minimum, skewness, and kurtosis, reflecting the diversity of the data sample across dimensions.

Table 2. Descriptive statistics of main variables.

Variable	Observation	Mean	Std	Min	Max	Skewness	Kurtosis
<i>Esg</i>	31479	1.385	0.292	0.000	2.079	−1.798	8.735
<i>ClimateRisk</i>	31479	0.162	0.084	0.000	0.789	0.872	4.348
<i>Up</i>	31479	0.180	0.069	0.025	0.437	0.346	2.782
<i>Down</i>	31479	0.247	0.207	0.004	0.865	1.239	3.985
<i>Network</i>	31479	0.427	0.215	0.045	1.089	0.877	3.616
<i>Indep</i>	31479	0.382	0.074	0.143	0.800	0.831	3.901
<i>Capital</i>	31479	0.647	0.666	−2.451	7.339	0.436	5.588
<i>Ppe</i>	31479	0.219	0.159	0.000	0.971	0.970	3.726
<i>Age</i>	31479	2.865	0.363	0.000	4.220	−0.873	5.390
<i>Roa</i>	31479	0.037	0.079	−2.834	0.786	−7.795	210.817
<i>Tobin</i>	31479	2.088	2.364	0.641	259.146	51.253	4846.793
<i>Share1</i>	31479	0.347	0.148	0.003	0.900	0.550	2.871
<i>Lev</i>	31479	0.430	0.204	0.007	0.998	0.178	2.278
<i>Tfp</i>	31479	6.842	0.896	2.629	11.479	0.616	3.676
<i>State</i>	31479	0.383	0.486	0.000	1.000	0.483	1.233

5. Empirical analysis

5.1. Baseline regression

Hypotheses H1a and H1b are tested using regression analyses based on Equations (1) and (2), respectively. Table 3 presents the baseline regression results. Columns (1) and (2) include only the core independent variables, while Columns (3) and (4) additionally incorporate the control variables. Columns (1) and (3) introduce the aggregate network spillover effect, whereas Columns (2) and (4) decompose the aggregate network spillover effect into upstream and downstream components.

The regression results show that in Columns (1) to (4), the estimated coefficient for *ClimateRisk* is significantly negative at least at the 10% confidence level, indicating that an increase in industry climate risk directly suppresses firm ESG performance. This provides support for Hypothesis H1a. Furthermore, in Columns (1) to (4), the coefficients for *Network*, *Up*, and *Down* are all highly significantly negative at the 1% confidence level. This suggests that industry climate risk inhibits firm ESG performance through upstream and downstream spillover effects within the production network, thereby validating Hypothesis H1b.

A closer examination reveals that the absolute value of the estimated coefficient for *Up* is larger, implying that climate risk shocks originating from the “supply side” are more harmful and exhibit stronger cascading amplification. The reason is that climate risks affecting upstream sectors may lead to disruptions in the supply of green raw materials to downstream firms. Such disruptions can be devastating for downstream firms in the production network that undertake ESG-related investments. This finding is consistent with the empirical conclusions of Li et al. (2025).

Regarding the control variables, the estimated coefficients for *Indep*, *Capital*, *Roa*, *Share1*, *Tfp*, and *State* are significantly positive. This indicates that improvements in firm governance structure, more intensive use of capital in the production process, stronger profitability, more concentrated ownership structure, higher production efficiency, and state ownership have significant positive effects on firm ESG performance. Conversely, the estimated coefficients for *Ppe* and *Lev* are significantly negative, suggesting that an excessively high proportion of fixed assets may indicate asset rigidity or that the firm operates in a traditional capital-intensive model, while a high asset-liability ratio reflects greater financial risk. Both factors adversely affect firm ESG performance.

Table 3. Baseline regression results.

	(1)	(2)	(3)	(4)
<i>ClimateRisk</i>	−0.056* (0.033)	−0.073** (0.034)	−0.068** (0.033)	−0.079** (0.034)
<i>Network</i>	−0.224*** (0.029)		−0.242*** (0.029)	
<i>Up</i>		−0.525*** (0.117)		−0.445*** (0.116)
<i>Down</i>		−0.228*** (0.029)		−0.245*** (0.029)
<i>Indep</i>			0.120*** (0.023)	0.120*** (0.023)
<i>Capital</i>			0.031*** (0.006)	0.031*** (0.006)
<i>Ppe</i>			−0.045** (0.020)	−0.046** (0.020)
<i>Age</i>			−0.024 (0.019)	−0.021 (0.019)
<i>Roa</i>			0.087*** (0.022)	0.087*** (0.022)
<i>Tobin</i>			−0.000 (0.001)	−0.000 (0.001)
<i>Share1</i>			0.093*** (0.023)	0.092*** (0.023)
<i>Lev</i>			−0.190*** (0.014)	−0.189*** (0.014)
<i>Tfp</i>			0.040*** (0.005)	0.040*** (0.005)
<i>State</i>			0.017* (0.010)	0.017* (0.010)
<i>Constant</i>			−0.242*** (0.029)	1.289*** (0.061)
Control Variables	NO	NO	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	31479	31479	31479	31479
<i>R</i> ²	0.011	0.011	0.024	0.025

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% confidence levels, respectively. Standard errors are reported in parentheses. The same applies to the following tables. Unless otherwise specified, the dependent variable is the log-transformed assigned ESG value.

5.2. Robustness checks

In this paper, we comprehensively employ robustness checks by replacing the measurement methods of key variables, adding control variables and adjusting the sample, and optimizing estimation methods. First, replacing the measurement methods of key variables: 1. Using logarithmic ESG scores instead of the original assigned ESG value as the dependent variable for re-estimation; 2. In addition to constructing the network spillover effect indicator based on the complete consumption coefficient matrix in the baseline regression, the direct consumption coefficient matrix is further adopted to reconstruct this indicator (*Network1*, *Up1*, *Down1*) and perform regression analysis. Second, adding control variables and adjusting the sample: 1. To mitigate omitted variable bias, firm size (*Scale*) and the shareholding ratio of the top ten shareholders (*Share10*) are included as control variables in the model; 2. Considering the potential systematic impact of the COVID-19 pandemic (2020–2022) on firm operations, samples from this period are excluded, and the estimation is reconducted to eliminate potential estimation bias caused by this public health event in the baseline regression results. Third, optimizing estimation methods: 1. Industry fixed effects are further incorporated into the model; 2. To eliminate the interference of outliers, all continuous variables are winsorized at the top and bottom 1%.

Table 4. Robustness checks 1: Alternative measures of key variables.

	(1)	(2)	(3)	(4)
	Alternative Dependent Variable: ESG Scores		Alternative Independent Variable: Measurement Based on Direct Consumption Coefficient Matrix	
<i>ClimateRisk</i>	−0.010 (0.007)	−0.012* (0.008)	−0.054* (0.032)	−0.056* (0.032)
<i>Network</i>	−0.061*** (0.007)			
<i>Up</i>		−0.102*** (0.026)		
<i>Down</i>		−0.061*** (0.007)		
<i>Network1</i>			−0.308*** (0.046)	
<i>Up1</i>				−0.306* (0.165)
<i>Down1</i>				−0.308*** (0.047)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	31479	31479	31479	31479
<i>R</i> ²	0.027	0.027	0.024	0.024

The results of the robustness checks are presented in Tables 4 to 6. The results indicate that after the aforementioned robustness treatments, the estimated coefficients of the core independent variables

(industry climate risk and the corresponding network spillover effect) remain largely negative and significant, which is broadly consistent with the results in Table 3. This confirms the robustness of the baseline regression results in this paper.

Table 5. Robustness Checks 2: Adding control variables and sample adjustments.

	(1)	(2)	(3)	(4)
	Adding Control Variables		Adjusting the Sample Period	
<i>ClimateRisk</i>	−0.061*	−0.073**	−0.203***	−0.209***
	(0.033)	(0.033)	(0.042)	(0.043)
<i>Network</i>	−0.223***		−0.173***	
	(0.029)		(0.044)	
<i>Up</i>		−0.445***		−0.283*
		(0.116)		(0.150)
<i>Down</i>		−0.226***		−0.173***
		(0.029)		(0.044)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	31479	31479	21585	21585
R^2	0.034	0.034	0.023	0.023

Table 6. Robustness Checks 3: Optimization of estimation methods.

	(1)	(2)	(3)	(4)
	Adding Industry FE		Winsorization	
<i>ClimateRisk</i>	−0.048	−0.057*	−0.060*	−0.072**
	(0.033)	(0.034)	(0.034)	(0.034)
<i>Network</i>	−0.253***		−0.233***	
	(0.030)		(0.030)	
<i>Up</i>		−0.418***		−0.423***
		(0.117)		(0.117)
<i>Down</i>		−0.254***		−0.241***
		(0.030)		(0.029)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Industry FE	YES	YES	NO	NO
N	31479	31479	31479	31479
R^2	0.030	0.030	0.024	0.025

5.3. Endogeneity analysis

Reverse causality between variables and sample selection bias are the core sources of endogeneity in the model. In this study, on one hand, industry climate risk impacts firm ESG performance directly

and through production network spillovers; however, firms with high ESG performance may inherently possess greater resilience to climate risk, creating a reverse causality concern. On the other hand, firms subjected to varying degrees of climate risk shocks may systematically differ in observable characteristics such as governance structure and asset allocation. If such sample self-selection issues driven by these factors are ignored, estimation results will be biased. To mitigate the aforementioned endogeneity issues, we employ the following three methods sequentially for testing: First, lagging the core independent variable and the dependent variable by one period to alleviate reverse causality in the time dimension between concurrent variables. Second, using the one-period lagged core independent variable and network spillover indicators calculated based on an invariant production network structure as instrumental variables and estimating the regression results using the instrumental variable approach. Third, employing the Propensity Score Matching (PSM) method to mitigate bias in estimation results caused by differences in observable sample characteristics. The procedure involves: First, divide the sample into treatment and control groups based on the median industry climate risk; second, use the set of control variables as matching variables and applying nearest-neighbor matching for propensity score matching; then, conduct a re-estimation based on the matched sample.

Table 7. Endogeneity analysis 1: Lagged core independent and dependent variables.

	(1)	(2)	(3)	(4)
	<i>Esg</i>		<i>L.Esg</i>	
<i>ClimateRisk</i>			−0.093** (0.038)	−0.103*** (0.038)
<i>Network</i>			−0.158*** (0.033)	
<i>Up</i>				−0.396*** (0.131)
<i>Down</i>				−0.159*** (0.033)
<i>L.ClimateRisk</i>	−0.087** (0.036)	−0.082** (0.037)		
<i>L.Network</i>	−0.194*** (0.035)			
<i>L.Up</i>		−0.103 (0.133)		
<i>L.Down</i>		−0.194*** (0.035)		
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	26776	26776	26776	26776
<i>R</i> ²	0.021	0.021	0.017	0.017

Table 8. Endogeneity analysis 2: Instrumental variable approach.

	(1)	(2)	(3)	(4)
	IV: Network Effect Indicator (One-Period Lag)		IV: Measurement Based on Invariant Production Network Structure	
<i>ClimateRisk</i>	−0.063* (0.033)	−0.057* (0.035)	−0.146*** (0.039)	−0.158*** (0.045)
<i>Network</i>	−0.213*** (0.034)		−0.524*** (0.078)	
<i>Up</i>		−0.256* (0.153)		−0.763* (0.390)
<i>Down</i>		−0.212*** (0.034)		−0.521*** (0.077)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Ac LM	2.0e+04***	1.6e+04***	3915.283***	2439.053***
CD Wald F	7.8e+04	1.8e+04	4559.576	1336.690
N	30580	30580	31059	31059
R^2	0.025	0.025	0.021	0.021

Table 9. Endogeneity analysis 3: PSM method.

	(1)	(2)
<i>ClimateRisk</i>	−0.105*** (0.037)	−0.119*** (0.037)
<i>Network</i>	−0.298*** (0.035)	
<i>Up</i>		−0.571*** (0.135)
<i>Down</i>		−0.299*** (0.035)
Control Variables	YES	YES
Firm FE	YES	YES
Year FE	YES	YES
N	24280	24280
R^2	0.026	0.026

The regression results from the above three endogeneity treatment methods are shown in Tables 7–9, respectively. It can be observed that after controlling for endogeneity, the coefficients of the core independent variables (industry climate risk and its network spillover effect) remain statistically significant and negative overall, indicating that the baseline regression conclusions of this paper are relatively robust. Notably, the instrumental variable results presented in Table 8 yield Cragg-Donald Wald F-statistics (e.g., 7.8e+04) that substantially exceed the weak identification critical values, decisively rejecting the null hypothesis of weak instruments. This confirms that the selected

instruments possess strong explanatory power for the endogenous variable. While the F-statistics are unusually large, this outcome largely stems from the instruments' strong predictive capacity for the endogenous regressor and the sample size, rather than indicating any econometric irregularities. Regarding the exclusion restriction, it is maintained that the instrumental variables influence firm ESG performance solely through their impact on industry climate risk exposure, thereby satisfying the exogeneity condition.

5.4. Heterogeneity analysis

This study demonstrates that rising industry climate risk adversely affects firm ESG performance through direct and production network spillover effects. However, whether the magnitude of these effects varies based on firm-specific characteristics, industry attributes, or temporal contexts remains an open and crucial question. To investigate these potential differential impacts, we conduct heterogeneity tests along the following four dimensions: firm size, ownership type, whether the production network is in an equilibrium state, and whether the firm operates in a high-carbon industry.

5.4.1. Firm size

Firm size may significantly moderate how industry climate risk, directly and via network spillovers, impacts ESG performance. To test this, we split the sample at the median of total assets, classifying firms above the median as large and those below as small. Table 10 presents the results. Notably, the negative impact of climate risk on ESG performance is stronger for large firms (columns (1) and (2) show significantly negative coefficients for direct and network effects, while only the network effect remains significantly negative in columns (3) and (4) for small firms).

Table 10. Heterogeneity analysis 1: Firm size.

	(1)	(2)	(3)	(4)
	Large		Small	
<i>ClimateRisk</i>	−0.141*** (0.045)	−0.147*** (0.046)	0.031 (0.057)	−0.008 (0.058)
<i>Network</i>	−0.225*** (0.038)		−0.237*** (0.059)	
<i>Up</i>		−0.352** (0.149)		−0.959*** (0.222)
<i>Down</i>		−0.225*** (0.038)		−0.246*** (0.059)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	18108	18108	13371	13371
<i>R</i> ²	0.015	0.015	0.048	0.049

This finding runs counter to the conventional view that larger firms, with greater resources and resilience, are less vulnerable to external shocks. Two potential explanations are proposed: First, large

firms face greater scrutiny from regulators, investors, and the public. Their operations and environmental footprints are more transparent, subjecting them to stricter compliance demands, higher disclosure expectations, and stronger societal pressure when climate risks intensify. Second, research shows that firms with higher network centrality experience stronger spillover effects (Miranda-Pinto et al., 2023). Large firms often occupy central positions in production networks, acting as hubs that aggregate and amplify climate risk shocks transmitted through supply and demand chains. This concentrated exposure exacerbates the decline in their ESG performance.

5.4.2. Ownership type

Ownership type is a critical governance dimension that influences a firm's resource endowment, objective function, and risk management logic, and it may systematically moderate the impact of climate risk on firm ESG performance. Table 11 reveals that compared to state-owned enterprises (SOEs), non-SOEs experience a more significant negative impact on their ESG performance when facing rising industry climate risk. This conclusion is supported by the regression results: Estimates based on the non-SOE sample show that the absolute values of the coefficients and their statistical significance for the direct effect and the production network spillover effect are markedly higher than those for the SOE sample. This indicates that the impact of industry climate risk on the ESG performance of non-SOEs is more pronounced in magnitude and certainty.

Potential reasons include: On one hand, SOEs often benefit from more stable policy support and resource guarantees, with their ESG practices closely aligned with policy objectives, thereby possessing stronger institutional resilience when confronting climate risks. On the other hand, non-SOEs are more constrained by market forces, where ESG investments are susceptible to profitability pressures and financing conditions, leaving them with limited flexibility and higher vulnerability in responding to climate risks. Consequently, the negative impact on their ESG performance is more substantial.

Table 11. Heterogeneity analysis 2: Ownership type.

	(1)	(2)	(3)	(4)
	SOE		Non-SOE	
<i>ClimateRisk</i>	-0.067 (0.052)	-0.066 (0.052)	-0.063 (0.044)	-0.082* (0.044)
<i>Network</i>	-0.212*** (0.039)		-0.275*** (0.044)	
<i>Up</i>		-0.204 (0.165)		-0.659*** (0.165)
<i>Down</i>		-0.212*** (0.039)		-0.277*** (0.044)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	12048	12048	19431	19431
R^2	0.023	0.023	0.039	0.039

5.4.3. Whether the production network structure is in equilibrium

The amplification effect on the transmission of negative shocks varies depending on whether the production network structure is in equilibrium. Dupor (1999) argued that the greater the overall dispersion of the input-output matrix, i.e., the more disequilibrated the production network structure, the stronger its amplification effect on transmitting negative shocks. To test this, we calculate the annual standard deviation based on the Leontief inverse matrix from 2009 to 2022. Using the median as a threshold, years with standard deviations below the median are defined as periods of equilibrated production network structure, and otherwise as periods of disequilibrated structure. Grouped regressions are then conducted for comparison. The regression results in Table 12 show that in the sample of disequilibrated periods, the absolute values and significance levels of the estimated coefficients for the direct effect and network spillover effect of industry climate risk are higher than those in the sample of equilibrated periods. This finding corroborates the results of Dupor (1999). In the context of this study, a disequilibrated production network structure significantly amplifies the negative impact of industry climate risk on firm ESG performance.

Table 12. Heterogeneity analysis 3: Whether the production network structure is in an equilibrium period.

	(1)	(2)	(3)	(4)
	Equilibrium Period		Disequilibrium Period	
<i>ClimateRisk</i>	−0.020 (0.053)	−0.020 (0.053)	−0.079 (0.049)	−0.115** (0.052)
<i>Network</i>	−0.232*** (0.045)		−0.275*** (0.041)	
<i>Up</i>		−0.294* (0.177)		−0.651*** (0.179)
<i>Down</i>		−0.229*** (0.046)		−0.293*** (0.042)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	21099	21099	10380	10380
R^2	0.027	0.027	0.023	0.024

5.4.4. Whether the firm belongs to a high-carbon industry

We further examine the heterogeneity in how firms respond to industry climate risk shocks based on whether they belong to a high-carbon industry². The results in Table 13 indicate significant differences in the transmission mechanisms of industry climate risk between high-carbon and non-high-carbon industries. Firms in high-carbon industries primarily experience significant negative impacts from production network spillover effects, while their direct effects are not pronounced. In contrast, although non-high-carbon

² Based on industry characteristics, industries with codes 4 through 30 in the Inter-Country Input-Output (ICIO) database are defined as high-carbon industries in this paper.

industry firms also exhibit some network effects, their significance and estimated coefficients are lower than those for high-carbon industries; however, their direct effects are significantly negative.

The potential reasons are as follows: High-carbon industries have long been at the core of climate policy regulation, and the direct transition pressures they face are largely anticipated; thus, the marginal effect of direct shocks is not significant. However, firms in high-carbon industries are often positioned upstream or at critical nodes in supply chains. When climate risks propagate through production networks, high-carbon firms bear compounded pressures from downstream, such as green procurement requirements and carbon cost transfers, resulting in particularly strong network spillover effects. In comparison, non-high-carbon industries primarily consist of non-physical sectors such as services and finance, which are not traditional focal points for pollution control, and their direct operations are weakly linked to carbon emissions. Nevertheless, as industry climate risks rise, such firms may also suddenly face direct constraints related to compliance and financing, leading to significantly negative direct effects. Moreover, as they are mostly in the mid-to-downstream segments of production networks, the supply chain transmission shocks they experience are relatively limited, resulting in weaker network effects.

Table 13. Heterogeneity analysis 4: Whether the firm belongs to a high-carbon industry.

	(1)	(2)	(3)	(4)
	High-Carbon Industry		Non-High-Carbon	
<i>ClimateRisk</i>	0.017 (0.039)	−0.000 (0.039)	−0.288*** (0.074)	−0.295*** (0.075)
<i>Network</i>	−0.362*** (0.041)		−0.123*** (0.043)	
<i>Up</i>		−0.804*** (0.149)		−0.269 (0.251)
<i>Down</i>		−0.360*** (0.041)		−0.123*** (0.043)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	25164	25164	6315	6315
<i>R</i> ²	0.026	0.026	0.039	0.039

6. Mechanism analysis and further discussion

6.1. Mechanism analysis

To verify the three mechanisms outlined in the theoretical and hypothesis sections, we construct the following econometric model:

$$M_{gt} = \alpha_0 + \alpha_1 ClimateRisk_{it} + \alpha_2 Network_{it} + \alpha_3 Control_{gt} + \mu_g + \lambda_t + \varepsilon_{gt} \quad (6)$$

$$M_{gt} = \alpha_0 + \alpha_1 ClimateRisk_{it} + \alpha_2 Up_{it} + \alpha_3 Down_{it} + \alpha_4 Control_{gt} + \mu_g + \lambda_t + \varepsilon_{gt} \quad (7)$$

In the equation, mechanism variables include: Firm Green Innovation: Measured as the natural logarithm of the total granted green patents (invention and utility model patents) plus one; Firm Financing Constraints: Proxied by the SA index (a negative value, where a lower value indicates more severe financing constraints); and Firm Systemic Risk: Proxied by the beta index (a higher value indicates greater systemic risk faced by the firm).

Among the mechanism variables, data on firm green innovation are sourced from the CNRDS database, while data on firm financing constraints and systemic risk are obtained from the CSMAR database.

Table 14 reports the regression results of the mechanism analysis. Columns (1) and (2) correspond to the green innovation mechanism, columns (3) and (4) to the firm financing constraints mechanism, and columns (5) and (6) to the firm systemic risk mechanism. It can be readily observed that in columns (1)–(4), the direct and network effects of industry climate risk are significantly negative at high confidence levels. This indicates that industry climate risk weakens firm green innovation and exacerbates financing constraints through direct and production network spillover effects, thereby inhibiting firm ESG performance. Thus, hypotheses H2 and H3 are supported.

Table 14. Mechanism analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
	Green Innovation		SA		Beta	
<i>ClimateRisk</i>	−0.905*** (0.091)	−0.776*** (0.092)	−0.058*** (0.009)	−0.077*** (0.009)	−0.037 (0.042)	−0.008 (0.043)
<i>Network</i>	−0.753*** (0.086)		−0.063*** (0.008)		0.067* (0.040)	
<i>Up</i>		−1.710*** (0.335)		−0.420*** (0.031)		0.617*** (0.156)
<i>Down</i>		−0.744*** (0.086)		−0.065*** (0.008)		0.069* (0.040)
Control Variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	24159	24159	24280	24280	24280	24280
R^2	0.229	0.231	0.871	0.872	0.287	0.288

Furthermore, in columns (5)–(6), although the direct effect of industry climate risk does not exhibit consistent significance, the network effect is significantly positive at least at the 10% level. This pattern aligns with the theoretical nature of systemic risk, namely, the co-movement and interconnectedness among firms, which is precisely the dimension of systematic risk that asset pricing models (Fama and French, 1993, 2015) seek to capture. The core of systemic risk lies in the co-movement between an individual entity and the broader market or system. The insignificance of the direct effect of industry climate risk precisely illustrates that the idiosyncratic volatility of a single industry is insufficient to directly destabilize firms' asset risk levels. What truly matters is that when an industry faces a climate shock, the risk propagates through supply chains, financial chains, or information chains to upstream, downstream, and other related industries. Ultimately, it is the resonance of the network that amplifies the systemic risk embedded in firm assets. This finding reveals the quintessential characteristic of climate

risk, where “a slight move in one part may affect the whole situation.” Therefore, the insignificant direct effect suggests that industry climate risk primarily impairs ESG performance by exacerbating this interconnected systemic vulnerability through network spillovers, rather than by directly altering individual firms’ risk profiles. Consequently, hypothesis H4 receives partial yet conceptually meaningful support, highlighting the role of production networks as a key transmission mechanism through which climate risk evolves into systemic risk. Collectively, these results validate hypotheses H2–H4, as proposed in this study.

6.2. Further discussion

As mentioned, firm ESG performance can be deconstructed and evaluated across three dimensions: Environmental (E), Social (S), and Governance (G) pertaining to ecological impact, stakeholder relations, and internal governance, respectively. Examining ESG performance solely at an aggregate level can obscure the differential responses of its individual dimensions to industry climate risk shocks. Therefore, decomposing firm ESG performance into these three dimensions for separate analysis enables a clearer revelation of the transmission pathways and heterogeneous effects of industry climate risk within the production network.

Table 15. Further discussion 1: Decomposition of ESG.

	(1)	(2)	(3)	(4)	(5)	(6)
	E Score		S Score		G Score	
<i>ClimateRisk</i>	−0.086*** (0.012)	−0.065*** (0.012)	−0.071*** (0.016)	−0.045*** (0.016)	−0.032*** (0.010)	−0.040*** (0.011)
<i>Network</i>	−0.047*** (0.011)		−0.133*** (0.014)		−0.031*** (0.009)	
<i>Up</i>		−0.333*** (0.043)		−0.328*** (0.056)		−0.172*** (0.037)
<i>Down</i>		−0.043*** (0.011)		−0.128*** (0.014)		−0.032*** (0.009)
Control Variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	31479	31479	31478	31478	31479	31479
R ²	0.104	0.107	0.078	0.080	0.126	0.127

The decomposition regression results presented in Table 15 indicate that industry climate risk exerts differentiated impacts on firm ESG performance through two mechanisms: direct shocks and production network transmission. The environmental dimension experiences the strongest direct impact. This is primarily because the environmental dimension is directly linked to carbon emissions and energy use, making it more susceptible to immediate and visibly rapid responses from direct industry climate risk shocks. In contrast, the social dimension exhibits the most pronounced network spillover effects. This phenomenon stems from the deep embedding of social performance within stakeholder relationships. Industry climate risk, when transmitted through the production network, can amplify downstream firms’ focus on supply chain social responsibility, labor rights, and firm reputation,

thereby significantly magnifying the network effects on the social dimension. Moreover, the governance dimension is relatively less affected under both mechanisms. This reflects the institutional inertia and adjustment lag inherent in governance structures, where changes tend to be long-term and indirect adaptive responses.

Researchers have decomposed the network spillover effects of industry climate risks from upstream and downstream perspectives but have not distinguished industry positions from the perspective of the value chain. Therefore, we further refer to the industry upstreamness measurement method proposed by Antràs et al. (2012) to classify industries into upstream and downstream to examine whether the impact of climate risk shocks on firm ESG performance differs significantly due to their different positions in the value chain. The measurement method for industry upstreamness is as follows:

$$UP_i = \frac{F_i}{Y_i} + 2 \times \frac{\sum_{j=1}^N \Omega_{ij} F_j}{Y_i} + 3 \times \frac{\sum_{j=1}^N \sum_{k=1}^N \Omega_{ik} \Omega_{kj} F_j}{Y_i} + 4 \times \frac{\sum_{j=1}^N \sum_{k=1}^N \sum_{l=1}^N \Omega_{il} \Omega_{lk} \Omega_{kj} F_j}{Y_i} + \dots \quad (8)$$

UP_i represents the upstreamness of industry i , while F_i , Y_i , and Ω_{ij} correspond to value-added, output value, and the direct consumption coefficient, respectively. Based on China's input-output database from 2009 to 2022, the upstreamness of each industry by year can be readily calculated. Furthermore, we use the median upstreamness as a threshold to classify industries into upstream and downstream categories. By aligning this classification with the micro-level data of firms based on their respective industries, the heterogeneous effects of industry climate risk shocks on firm ESG performance are systematically examined from the perspective of value chain position.

Table 16 reports the grouped regression results for upstream and downstream industries. The research indicates that the impact of industry climate risk on firm ESG performance exhibits significant heterogeneity based on value chain positioning. In terms of direct effects, industry climate risk has a significant positive impact on the ESG performance of upstream firms while it shows a significant negative impact on downstream firms. This difference may stem from the distinct pressure response logics of upstream and downstream firms: Upstream firms, being directly situated at critical nodes of climate policies and supply chain transformation, may proactively integrate climate risk responses into their strategic planning in accordance with the “green transition hypothesis.” The environmental regulations triggered by transition risks may compel these firms to enhance green innovation (Berrone et al., 2013), thereby improving their ESG performance. This compulsion effect parallels the findings of Naseer et al. (2026), who discovered that higher-emitting firms tend to bolster their ESG ratings chiefly through enhanced transparency and governance practices. In contrast, downstream firms are more susceptible to direct shocks from rising compliance costs and market demand fluctuations, leading to a short-term decline in their ESG investments and ratings. Regarding network effects, regardless of whether firms are positioned upstream or downstream in the value chain, the production network exerts a significant negative transmission effect on their ESG performance. This result suggests that the shocks caused by industry climate risk through the production network channel are not unique to downstream firms. As indicated by the “Bullwhip Effect” (Lv et al., 2020), shocks experienced downstream accumulate progressively along the industrial chain, exerting a negative impact on the ESG performance of upstream firms as well.

Table 16. Further discussion 2: Considering value chain positioning.

	(1)	(2)	(3)	(4)
	Upstream Industry		Downstream Industry	
<i>ClimateRisk</i>	0.297*** (0.066)	0.291*** (0.066)	−0.196*** (0.040)	−0.206*** (0.041)
<i>Network</i>	−0.212*** (0.046)		−0.316*** (0.061)	
<i>Up</i>		−0.582** (0.232)		−0.560*** (0.144)
<i>Down</i>		−0.229*** (0.047)		−0.260*** (0.067)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
N	14641	14641	16838	16838
R^2	0.030	0.031	0.028	0.028

Research has confirmed that firm investment efficiency significantly inhibits risk (Wu et al., 2023). Therefore, we further examine whether investment efficiency plays a moderating role in the process by which industry climate risk affects firm ESG performance. The approach is as follows: First, drawing on the method proposed by Richardson (2006), the degree of inefficient investment is calculated for each firm. Then, the opposite value of this measure is taken to define the level of firm investment efficiency. Finally, an interaction term between firm investment efficiency and the core independent variable is constructed and incorporated into the econometric models (1) and (2) for re-estimation.

Table 17 reports the regression results for the moderating effect of investment efficiency. The non-interaction term for industry climate risk remains significantly negative, but the coefficients of the interaction terms are not statistically significant. This finding initially suggests that while the negative impact of industry climate risk persists in the full sample, investment efficiency may have a potential moderating effect on this relationship. To further verify this moderating effect, we divide firms into high- and low-investment efficiency groups based on the median and perform subsample regressions. The results in columns (3)–(6) show that the negative impact of industry climate risk is more significant in the low-investment efficiency group, while its effect is relatively weaker in the high-efficiency group. This indicates that firms with higher investment efficiency can effectively mitigate the systemic pressure of industry climate risk on their sustainable performance through better resource allocation and strategic adjustments, thereby exhibiting notable cross-group heterogeneity in the subsample analysis. Overall, although the interaction term is insignificant, the subsample regression results provide further evidence that support the moderating role of investment efficiency.

Table 17. Further Discussion 3: The moderating effect of investment efficiency.

	(1)	(2)	(3)	(4)	(5)	(6)
			High-Investment Efficiency		Low-Investment Efficiency	
<i>ClimateRisk</i>	−0.078** (0.037)	−0.087** (0.037)	−0.191*** (0.049)	−0.205*** (0.050)	−0.201*** (0.067)	−0.222*** (0.068)
<i>ClimateRisk</i> × <i>Inveff</i>	−0.070 (0.189)	−0.007 (0.197)				
<i>Network</i>	−0.237*** (0.031)		−0.288*** (0.047)		−0.338*** (0.063)	
<i>Network</i> × <i>Inveff</i>	0.041 (0.061)					
<i>Up</i>		−0.462*** (0.123)		−0.522*** (0.183)		−0.830*** (0.242)
<i>Up</i> × <i>Inveff</i>		−0.103 (0.145)				
<i>Down</i>		−0.239*** (0.031)		−0.289*** (0.047)		−0.338*** (0.063)
<i>Down</i> × <i>Inveff</i>		0.110 (0.088)				
Control Variables	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	28329	28329	13392	13392	10888	10888
<i>R</i> ²	0.022	0.022	0.029	0.029	0.026	0.027

7. Conclusions and policy recommendations

In this study, we examine how industry climate risk affects firm ESG performance through production networks, using data from Chinese A-share listed companies (2009–2022). Key findings indicate that such risk significantly reduces ESG performance via direct and network spillover effects, with upstream spillovers being particularly strong. The negative impact is more severe for large firms, non-state-owned enterprises, and during periods of imbalanced network structure. Mechanism analysis shows that climate risk undermines ESG by weakening green innovation, tightening financing constraints, and increasing systemic asset risk, all amplified by the production network. Further analysis reveals that the environmental dimension is most sensitive to direct shocks, while the social dimension responds more to network effects. A value-chain perspective shows that upstream firms face negative network spillovers but a positive direct effect, whereas downstream firms suffer a dual negative impact. Higher investment efficiency can mitigate these effects.

The core contribution of this paper lies in integrating industry climate risk, production networks, and firm ESG performance into a unified analytical framework. From the perspective of production network spillovers, we systematically examine how climate risk transmits through input-output linkages to influence firm ESG performance, thereby elucidating the transmission pathways and underlying mechanisms at this interdisciplinary intersection. This framework not only reveals the heterogeneous

effects across ESG dimensions but also uncovers the asymmetric impacts along value chains, offering novel insights into the indirect ripple effects of climate risk beyond direct firm-level exposure.

However, this study has several limitations regarding the construction of industry-level climate risk measures. Specifically, when aggregating firm-level climate risk to the industry level, no weighting is applied based on market size or market share. This approach may introduce systematic bias, as larger firms with greater market power might have a disproportionate influence on industry-wide dynamics. Researchers could refine this measure by incorporating semantic analysis and developing more sophisticated, size-weighted aggregation schemes.

These findings yield important implications. For managers, they highlight the need for supply chain due diligence and investment efficiency to buffer climate shocks. For investors, they provide a framework for assessing portfolio climate risk across supply chains. For policymakers, the results support three interventions: Establishing digital monitoring platforms for key industrial chains, providing tailored support to vulnerable firms (particularly downstream), and implementing coordinated policies addressing green innovation, financing constraints, and systemic risk hedging.

Author contributions

Junfan Ren: Writing—original draft, Writing—review & editing, Supervision, Funding acquisition.

Taofeng Chen: Conceptualization, Methodology, Validation, Formal analysis.

Zhihao Hu: Software, Formal analysis, Data Curation.

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Use of AI tools declaration

No AI tools were used in the writing or preparation of this manuscript.

Conflict of interest

All authors declare no conflicts of interest in this paper.

Data Availability Statement

The data used in this study are not available for public access because they are reserved for future research. Reasonable requests may be directed to the corresponding author.

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