

Climate Shocks and Systemic Risks in the Real Economy

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Abstract. As global warming becomes increasingly severe, frequent extreme weather events and the accelerated transition to a low-carbon economy have made climate shocks a significant factor affecting the operation of the real economy and the stability of financial markets. This paper uses data from Chinese A-share listed companies from 2007 to 2024 as the initial research sample to empirically examine the impact of climate shocks on the systemic risk of real enterprises. The study finds that climate shocks significantly increase corporate systemic risk, and this conclusion remains valid after a series of robustness tests. Mechanism analysis indicates that climate shocks amplify systemic risk by exacerbating financial distress, reducing production efficiency, and worsening information asymmetry. Heterogeneity analysis shows that green finance reforms, climate finance innovations, and green fiscal policies effectively mitigate the adverse transmission of climate shocks to corporate systemic risk by alleviating information asymmetry, providing risk hedging tools, and enhancing corporate resilience. Moderation analysis reveals that ESG performance significantly mitigates the positive impact of climate risk on corporate systemic risk. This risk-mitigating effect primarily stems from substantial contributions from the environmental (E) and governance (G) dimensions, while the social (S) dimension plays a negligible role. Further analysis indicates that the upward pressure of climate risk on systemic risk in the real economy is primarily driven by transition risk, with the impact of physical risk being relatively limited. These findings align with the logic that climate shocks ultimately elevate systemic risk by deteriorating corporate operations and financial conditions and exacerbating risk transmission. This conclusion provides theoretical references and practical insights for regulators to improve climate risk prevention and control systems, guide enterprises in proactively managing climate risks, and guard against systemic financial risks.

Keywords: Climate shocks; Systemic risks in the real economy; Financial distress; ESG; Transition risks.

1. Introduction

In recent years, frequent extreme weather events worldwide have not only posed serious challenges to ecological security and human health but have also become a major source of risk threatening the stability and development of the financial system. *The Global Risks Report 2025* notes that environmental risks dominate the long-term outlook, with extreme weather events ranking among the top risks for the coming decade. Without effective intervention, climate change risks will materialize into real threats, with potential consequences that could even exceed those of traditional financial crises. Consequently, climate-related financial risks are widely recognized as a major source of systemic financial risk. How to prevent systemic risks in financial markets while promoting the development of green finance and supporting the transition to a green, low-carbon economy has also garnered high-level attention from Party and state leaders. In September 2025, General Secretary Xi stated in his address at the *United Nations Climate Change Summit* that “addressing climate change is an urgent and long-term task.” Against this backdrop, a thorough examination of how climate shocks spread to real-economy enterprises and evolve into systemic risks holds significant practical importance for preventing and defusing major crises and achieving a smooth economic transition.

Climate change has multifaceted implications for financial stability, and its impact is gradually spreading from specific sectors to the entire real economy. As the core microeconomic agents of economic activity, real enterprises not only face increasing uncertainty in production and operations due to extreme climate shocks (Pankratz et al., 2024), but their industrial collaboration systems—

given their complex structures and deep interconnections—have also become key pathways for the amplification and transmission of extreme climate risks.

When subjected to climate shocks, enterprises' factor of production systems suffer significant negative effects. Such shocks first impact existing capital, not only causing substantial damage to physical assets but also severely disrupting normal production and business operations as well as the process of capital accumulation (Tan & Gao, 2020; Gu & Zhang, 2023). At the same time, climate risks permeate the financial system through channels such as asset impairment and supply chain disruptions, significantly amplifying volatility in financial markets. This leads to a sharp contraction in the risk appetite of market participants, triggering herd behavior and, consequently, systemic financial instability. Furthermore, the impacts of climate change are reflected at the level of production efficiency: its effects on total factor productivity (*TFP*) in the agricultural sector exhibit significant regional heterogeneity; within the non-agricultural sector, highly polluting industries in the manufacturing sector suffer particularly severe negative impacts due to the frequent occurrence of extreme weather events (Burke et al., 2015). At the same time, firms with higher exposure to climate risks tend to exhibit lower leverage ratios. This phenomenon is primarily attributed to increased volatility in corporate revenues caused by climate risks, reduced access to external financial resources, and a significant rise in debt financing costs (Ginglinger & Moreau, 2019).

To address the profound impacts of climate change on the natural environment and effectively mitigate the potential shocks of climate risks, countries worldwide are accelerating the transition to a low-carbon economy. However, scholars have noted that, in addition to the threat of “physical risks,” we also face severe “transition risks.” This risk stems from the process of transitioning the economy to a low-carbon model. As governments tighten policies to address climate change, technologies rapidly evolve, and market preferences shift, the profitability of relevant enterprises may be impacted, leading to the rapid accumulation of financial risks in the context of climate change (Hansen, 2022). Transition risk is not a short-term fluctuation but a long-term structural challenge spanning decades. Its impact is primarily concentrated in industries with a high risk of stranded assets, particularly the fossil fuel industry chain (Zhang et al., 2022). In its 2020 forecast, the International Energy Agency (IEA) warned that if the global low-carbon transition accelerates, high-carbon industries could face stranded assets amounting to as much as \$10 trillion, a figure that could rise to as high as \$28 trillion by 2100 (IEA, 2020). This not only implies that the balance sheets of relevant industries will face immense pressure but also directly leads to a significant decline in the value of investment portfolios held by companies with these high-carbon assets. Furthermore, the latest academic research indicates that transition risks and the accompanying policy adjustments often cause severe shocks to the financial system. These shocks are continuously amplified through the credit networks formed by financial institutions such as banks via the financial accelerator effect, thereby triggering broader systemic financial risks (Yang et al., 2024).

Based on previous literature on climate risks, frequent extreme weather events not only cause direct damage to physical assets, but the tightening of policies and technological advancements during the low-carbon transition also pose the risk of asset stranding. The combined effect of these factors significantly exacerbates systemic risks for real economy enterprises, posing a serious challenge to financial stability. Therefore, a thorough examination of this transmission mechanism is crucial for comprehensively mitigating systemic risks in the real economy.

Building on this, this paper conducts an empirical analysis using Chinese A-share listed companies from 2007 to 2024 as the initial research sample. The results confirm that climate shocks (*CR*) have a significant positive impact on systemic risk in the real economy (*MES*), and this conclusion remains robust after changing the sample, employing various measurement methods for variables, and using instrumental variables to address endogeneity issues. Heterogeneity analysis indicates that the implementation of policies in Green Finance Pilot Zones, Climate Finance Pilot Zones, and Fiscal Demonstration Cities for Energy Conservation and Emission Reduction significantly mitigates the positive impact of climate shocks on systemic risk in the real economy. In summary, these findings

are highly consistent with the core argument that “climate shocks can increase corporate systemic risk.”

The contributions of this paper include the following: First, it expands the research on the economic consequences of climate risk. By empirically testing the positive impact of climate shocks on corporate systemic risk, the paper reveals a three-fold transmission mechanism at the firm level—involving “financial distress, production efficiency, and information asymmetry”—thereby enriching the theoretical framework of the microeconomic consequences of climate risk. Second, it deepens the research on the impact of climate shocks on the systemic risk of real-economy firms. This paper incorporates climate factors into the analytical framework for the causes of corporate systemic risk and empirically verifies that climate shocks are a significant exogenous variable that exacerbates corporate systemic risk. At the same time, by introducing ESG performance as a moderating variable, the study identifies the key role of the environmental (E) and governance (G) dimensions in mitigating the impact of climate risks. Third, it provides practical policy insights for regulators and market participants in addressing climate risks, holding significant practical implications. The study provides empirical evidence to support regulators in utilizing policy tools—such as green finance reform and innovation pilot zones, climate finance pilot zones, and fiscal demonstration cities for energy conservation and emissions reduction—to establish a differentiated regulatory framework, improve climate risk hedging instruments, and strengthen disclosure systems. This will help effectively prevent systemic financial risks during the process of achieving the “dual carbon” goals.

The structure of this paper is as follows: Section 3 presents the theoretical analysis and research hypotheses; Section 4 outlines the research design; Section 5 details the main empirical tests and analysis; Section 6 presents further mechanism tests; and Section 7 concludes the study.

2. Literature review

2.1. Research on the Economic Consequences of Climate Risks

To accurately assess the impact of climate change on the financial system, academics and authoritative institutions have engaged in in-depth discussions regarding the concept and classification of climate-related financial risks. The Bank for International Settlements (BIS) was among the first to introduce the concept of the “green swan,” specifically to describe the systemic financial risks that may arise from extreme events triggered by climate change. Building on this, the Network for Greening the Financial System (NGFS) has further systematically categorized climate-related risks into climate physical risks and climate transition risks (Ma & Sun, 2020).

Climate physical risks are primarily triggered by extreme weather events or long-term shifts in climate patterns. Extreme meteorological disasters exacerbated by global warming not only directly threaten human health but also cause widespread crop yield reductions, jeopardizing global food security (Zhao et al., 2017). Furthermore, frequent extreme weather events can damage public infrastructure, leading to disruptions in supply chains and transportation networks (Sampson, 2017), thereby weakening economic fundamentals at the macro level. At the corporate level, the impact of physical risks is even more direct. Natural disasters can destroy a company’s physical assets, such as factories and equipment, leading to production halts and, consequently, a decline in total factor productivity (Wang, 2024). The operational difficulties faced by real-economy enterprises ultimately spill over into financial assets. These risks spill over primarily through two channels: first, the credit channel, wherein corporate defaults trigger a surge in non-performing loans at banks; and second, the market sentiment channel, wherein disasters provoke panic selling by investors, leading to abnormal fluctuations in asset prices (Yang et al., 2024).

Climate transition risk refers to financial risks arising from stricter policies, technological innovations, or shifts in market preferences during the transition to a low-carbon economy. Transition risk is considered the most significant climate risk (Zhang et al., 2022). On the one hand, while policy tools such as carbon taxes, carbon emission quotas, and renewable energy subsidies effectively mitigate

physical risks and enhance an economy's resilience to extreme climate shocks, the transition risks they trigger must not be overlooked. These policies may lead to significant asset devaluation in high-carbon-intensive industries such as oil, coal-fired power, and steel, exacerbating the risk of "stranded assets" and consequently causing a sharp decline in portfolio value (van der Ploeg & Rezai, 2020). Against the backdrop of stricter regulations, high-emission enterprises will face dual pressures from environmental penalties and rising carbon quota costs, resulting in soaring operating costs, shrinking profit margins, and downward revisions in market valuations. At the same time, as the economy transitions toward a green and low-carbon model, energy-intensive and high-emission enterprises are facing significant transformation pressures. Equipment upgrades and technological advancements not only require massive R&D investments but also drive up the costs of acquiring fixed assets (Gao et al., 2022; Tan & Gao, 2020). On the other hand, as transition risks continue to accumulate and the uncertainties of climate change become increasingly apparent, potential investors' willingness to invest in climate-sensitive enterprises has significantly diminished. At the same time, green and low-carbon concepts are becoming deeply embedded in consumer behavior, prompting market participants to favor financial assets and related enterprises with favorable climate conditions and outstanding environmental performance. This growing preference for environmentally friendly enterprises significantly exacerbates the risk of a sharp decline in the asset values of carbon-intensive enterprises (Chen et al., 2020), thereby increasing the instability of the financial system and potentially having adverse effects on systemic risk (Monasterolo, 2020).

2.2. Research on Systemic Risks in the Real Economy

Since the 2008 global financial crisis, "systemic risk" has remained a hot topic in both academic and practical circles. At the macro level, it refers to both the complete loss of the financial system's basic functions and the phenomenon in which a shock to a single market or entity within the system, through spillover effects, continuously accumulates and spreads to other parts, ultimately endangering the entire system (Zhang et al., 2022). At the micro level, it refers to market risk—an inherent risk that cannot be eliminated by constructing a diversified portfolio (Lee C. F. & Lee A. C., 2006). The Financial Stability Board (*FSB*) notes that contagion is a key criterion for assessing systemic financial risk. This risk arises from the combined effects of internal and external factors within the system, transmitting negative effects to a broader scope through a dynamic process (Sun et al., 2019)—that is, various forms of externalities. Thus, spillover effects are a prominent feature of systemic risk.

Currently, academic community has shifted its focus in measuring systemic financial risk from traditional metrics such as Value at Risk (*VaR*) and Expected Shortfall (*ES*) to an increasing emphasis on the interconnections between financial markets and their risk transmission mechanisms, leading to the development of a wide range of metrics for quantifying systemic financial risk. (Li, M. H., & Huang, Y. B., 2017). Among these, mainstream research methods include Conditional Value at Risk (*CoVaR*) (Adrian & Brunnermeier, 2011), Marginal Expected Shortfall (*MES*) (Acharya et al., 2017), Component Expected Shortfall (*CES*) (Banulescu & Dumitrescu, 2015), and the Systemic Risk Index (*SRISK*) (Brownlees & Engle, 2017).

At present, China is at a critical stage in preventing and defusing major risks. The reason why real-economy enterprises have become a key source of systemic risk lies in their growing vulnerability and increasing systemic interconnectedness (Li et al., 2023). On the one hand, high-debt and high-leverage business models are the fundamental drivers that exacerbate the vulnerability of non-financial enterprises and thereby endogenously generate systemic risk (Alfaro et al., 2017). Although China has implemented a series of robust deleveraging policies, the inherent conflict between deleveraging and maintaining economic growth, coupled with "pseudo-deleveraging" practices—such as leverage manipulation by real economy enterprises to comply with regulatory requirements (Xu et al., 2020)—has led to a significant slowdown in the deleveraging process of China's non-financial corporate sector, further exacerbating its endogenous vulnerability. On the other hand, with the increasing prevalence of economic phenomena such as credit guarantees, informal investment and financing, and financialization-driven herd behavior, coupled with the deep interweaving of supply

chains and industrial chains, the network connections among China's real enterprises have become increasingly tight and complex. As risk interlinkages between the real and financial sectors continue to strengthen, financial market risks will create a "spiral" of mutual contagion between the two sectors through a "systemic risk linkage mechanism" (Liu & Li, 2021). This highly interconnected network structure leaves real economy enterprises collectively exposed to systemic risks that are difficult to mitigate. Once a key node enterprise within the network suffers a negative shock, the resulting tail risk is highly likely to generate a cascade effect through the network, triggering a "domino effect" (Li et al., 2025), rapidly spreading throughout the entire system and ultimately inducing systemic risk. The credit contraction triggered by systemic risk will weaken the liquidity and debt-repayment capacity of some enterprises, thereby increasing the probability of their falling into financial distress. At the same time, enterprises often rely on equity pledges to raise working capital; however, the decline in stock prices caused by systemic risk will subject such enterprises to margin call pressures (Pang et al., 2020), thereby inducing liquidity risk. In severe cases, this may even lead to a breakdown in the capital chain, triggering a corporate financial crisis.

2.3. Research Review

In summary, existing research has largely focused on assessing the micro-level impacts of climate risks on individual firms—such as credit ratings and stock price volatility—while offering few discussions from a macro perspective on the systemic risks posed to the real economy by climate shocks. As the microfoundation of macroeconomic operations, the climate shocks faced by real firms exhibit strong interconnectivity and spillover effects. Assessing only the isolated impact of climate risks on individual firms, while ignoring the contagion effects of risks spreading across firms through channels such as supply chains and financial linkages, can easily lead to an underestimation of the overall risk exposure of the economic and financial system. Current research remains insufficient in discussing the transmission mechanisms and governance boundaries of systemic risks in the real economy caused by climate shocks. While climate shocks are a significant source of systemic risk, the underlying mechanisms through which they permeate the micro-enterprise level and evolve into systemic risk require further clarification. Based on the aforementioned research context and theoretical logic, this paper will conduct an in-depth exploration of the transmission mechanisms and intrinsic relationship between climate change and corporate systemic risk. This will not only help clarify the financialization pathways of climate risk at the micro-enterprise level—thereby enabling a comprehensive understanding of the policy effectiveness of climate risk management systems and a deeper grasp of the generation and evolution logic of systemic risk in the real economy—but will also provide important theoretical foundations and practical guidance for preventing the excessive accumulation of systemic risk in the real economy from threatening stable economic growth, as well as for regulatory authorities in building a climate-resilient financial system.

3. Theoretical Analysis and Research Hypotheses

The mechanism underlying the formation of systemic risk in the real economy can be broken down into two core dimensions: first, the "accumulation of individual tail risks" within individual firms, and second, "systemic interconnections" among firms (Li et al., 2025). As a specific type of external shock, climate shocks can act on both of these dimensions simultaneously, thereby leading to the accumulation and diffusion of systemic risk.

At the level of individual tail risk, the damage caused to enterprises by extreme climate events exhibits significant nonlinearity and fat-tail characteristics. Unlike general business fluctuations, climate physical shocks are sudden, unpredictable, and highly destructive; they can drastically worsen an enterprise's balance sheet within a short period, directly increasing the probability of default. Research confirms that physical climate shocks significantly increase corporate default risk by hindering business development capabilities and causing disorderly revaluation of assets (Wang, 2025). At the same time, climate transition risks further exacerbate the default pressures faced by firms through rising policy uncertainty and stricter carbon pricing (Chen et al., 2023).

At the systemic level, climate shocks amplify risk contagion among firms through multiple network channels. First, the internal economic networks of real-economy firms constitute a key channel for the propagation of shocks. When a climate disaster strikes a node in the supply chain, upstream and downstream firms are affected through mechanisms such as order disruptions and defaults on accounts receivable. Second, climate shocks exhibit a “shared exposure” characteristic; firms within the same region or industrial chain often face similar climate risk exposures. This leads to increased correlation in asset returns across firms and significantly raises the probability of credit contagion. Because climate shocks are widespread, long-lasting, and capable of simultaneously activating multiple contagion channels, they transform localized physical damage into systemic financial risk. Therefore, this study proposes the following hypothesis.

H1: Climate shocks amplify systemic risk in the real economy.

The transmission mechanism through which extreme weather events trigger a surge in systemic corporate risk exhibits complex and multidimensional characteristics. First, the physical impact of climate disasters directly leads to issues such as damage to corporate fixed assets, loss of inventory, and difficulties in collecting accounts receivable. These asset-side losses are rapidly reflected on the balance sheet through the capital market’s mechanism of “disorderly revaluation of asset values,” thereby increasing corporate default risk (Wang, 2025). Furthermore, the sharp deterioration of a firm’s book value exacerbates the deterioration of financial indicators; for instance, the decline in market capitalization triggered by falling stock prices further weakens financial soundness. At the same time, production disruptions and customer attrition caused by climate shocks result in a sharp decline in revenue, while post-disaster reconstruction and emergency expenditures generate a sudden surge in funding needs. This “revenue-expenditure” mismatch effect is highly likely to trigger a liquidity crisis, forcing firms to rely on high-cost short-term financing to maintain operations, thereby passively increasing financial leverage. Relevant research indicates that high leverage and credit mismatches are key factors exacerbating systemic corporate risks (Li et al., 2023). More critically, exposure to climate risks triggers risk-averse behavior among financial institutions; the resulting credit crunch leads to a non-linear intensification of financing constraints for affected enterprises, creating a vicious cycle of “climate shocks → financial deterioration → financing constraints → deepening crisis.” When climate shocks are concentrated in specific regions or industries, the simultaneous financial distress faced by a large number of companies can trigger a contagion of credit risk, ultimately transforming a localized financial crisis into a systemic credit crisis. The cumulative amplification of this domino effect means that the macroeconomic impact of climate shocks extends far beyond the level of individual companies.

H2: Climate shocks exacerbate financial distress, thereby increasing systemic risk for firms.

Climate shocks trigger declines in corporate productivity through multiple mechanisms, thereby increasing systemic risk. Climate events such as extreme heat, floods, and typhoons directly damage production facilities, disrupt logistics and transportation, and cause labor absences, resulting in an immediate decline in corporate output capacity. Such direct production disruptions directly hinder firms’ operational and growth capabilities. Research by Wang (2025) confirms that physical climate shocks significantly increase firms’ default risk through this channel. Furthermore, in the long term, frequent climate shocks lead to the loss of human capital, the scrapping of technological equipment, and the impairment of intangible assets, forcing resources to shift from innovation and R&D toward post-disaster recovery, resulting in a structural decline in total factor productivity. This collective decline in production efficiency translates into systemic risk primarily through two channels. First, weakened profitability reduces firms’ debt-repayment capacity, increasing the probability of debt default, which then spreads to credit-linked financial institutions and affiliated enterprises. Second, the decline in output triggers a reduction in revenue, which generates a multiplier effect through the aggregate demand channel. Insufficient upstream supply constrains downstream production, creating a negative feedback loop that exacerbates the vulnerability of the economic system. When a majority of firms simultaneously experience efficiency losses, macroeconomic systemic vulnerability rises sharply, significantly increasing the probability of triggering the critical threshold for systemic risk.

H3: Climate shocks increase systemic risk for enterprises by reducing production efficiency.

Losses incurred by enterprises due to climate disasters are difficult to assess and manifest with a time lag; their full impact takes a considerable amount of time to be fully reflected in financial statements. This information asymmetry makes it difficult for external investors and creditors to accurately assess the true risk profile of enterprises, leading to a sharp deterioration in the information environment. As the concept of the “green swan” reveals, climate change may give rise to financial risk events characterized by extreme uncertainty (Yang et al., 2024). Furthermore, information asymmetry following climate shocks further exacerbates adverse selection and moral hazard. Specifically, high-risk firms have a stronger incentive to conceal the true extent of their losses to maintain access to financing, while firms receiving rescue funds may reduce their investment in risk prevention and control. This, in turn, drives up overall financing costs and undermines the allocative efficiency of credit markets. Consequently, the intensification of information asymmetry prevents the market from effectively distinguishing between affected and unaffected firms. Negative information may be excessively generalized to the entire industry or market, triggering panic selling and liquidity shortages. Simultaneously, information asymmetry leads to systematic biases in investors’ assessments of systemic risk; a surge in risk premiums causes asset prices to spiral downward, and liquidity tightening is further amplified through the financial accelerator mechanism. The low-frequency, high-impact nature of climate shocks further deprives the market of historical experience to anchor risk assessments. Under conditions of information asymmetry, this fosters overreactions and the chain transmission of risks, ultimately transforming localized information frictions into systemic risk crises (Fang & Peng, 2025).

H4: Climate shocks increase corporate systemic risk by exacerbating information asymmetry.

4. Research Design

4.1. Sample Selection and Data Sources

This study uses Chinese A-share listed companies from 2007 to 2024 as the initial research sample and processed the sample as follows: First, samples from the financial and insurance sectors were excluded; second, samples with missing variable data were excluded; third, samples classified as ST, *ST, or PT were excluded; and fourth, to mitigate the impact of outliers, all continuous variables were trimmed at the 1% percentile at both ends. Corporate data was sourced from the Guotai-An database (CSMAR), while text data was obtained from the Juchao Information Network.

4.2. Definitions of Key Variables

1. Dependent variable: Systemic risk of corporate entities (*MES*)

Drawing on the work of Acharya et al. (2017), this paper employs marginal expected loss as a proxy for systemic risk in the corporate sector. By measuring the expected loss of a specific firm when the market enters an extreme downturn, this metric effectively captures the extent of systemic risk exposure at the firm level. Its core logic lies in assessing a firm’s potential contribution to overall systemic risk from the perspective of its own vulnerabilities.

2. Key explanatory variable: Climate shock (*CR*)

Climate shocks at the firm level refer to the dual impacts faced by firms—both short-term extreme weather events and long-term shifts in climate patterns—as viewed from a micro-firm perspective. Constructing indicators based on this micro-level perspective can effectively capture the individual characteristics of different firms and the heterogeneity of climate shock intensity at the micro-level, thereby enabling a more precise identification of the actual extent of shocks borne by firms. This paper uses the frequency of climate-related terms in corporate annual reports as a measure of the severity of climate shocks at the firm level. Drawing on the research approach of Du et al. (2023) and drawing from the English climate dictionary constructed by Lietal. (2020), this study accounts

for differences in Chinese and English linguistic contexts. By reviewing a selection of corporate annual reports, the study supplemented the dataset with a more diverse range of climate-related keywords specific to the Chinese context. Additionally, by integrating relevant terminology from the National Meteorological Science Data Center and the *China Meteorological Disaster Yearbook*, the study ultimately constructed the “seed word set” for climate shocks used in this analysis. Building on this foundation, this study utilizes the Wingo financial text data platform and deep learning algorithms to identify the top 10 most similar terms to the seed terms. After excluding obviously irrelevant terms, the seed terms were expanded to form an extended vocabulary for measuring corporate climate impacts.

3. Mechanism Variables

Based on the theoretical analysis and research hypotheses presented earlier, this paper selects the following mechanism variables.

First is financial distress. Existing literature offers a wide range of indicators for measuring corporate financial risk. Compared to single indicators such as the debt-to-equity ratio, the Z-score model provides a more comprehensive assessment of a firm’s working capital, retained earnings, profitability, and asset turnover. Therefore, this paper selects the Z-score as a proxy variable for measuring a firm’s financial risk and distress level. A higher Z-score indicates greater financial soundness and a lower probability of the firm falling into financial crisis or bankruptcy.

Second is production efficiency. The academic community generally adopts total factor productivity (*TFP*) as the core indicator for characterizing the production efficiency of individual firms. Regarding the choice of specific estimation methods, since traditional OLS estimation is prone to endogeneity issues such as cointegration, this paper employs the LP method to estimate the total factor productivity of listed companies. A higher value of this indicator signifies higher production efficiency.

Third is information asymmetry. Existing research typically uses the degree of earnings management or analyst attention to indirectly reflect the information environment, but these measures are often susceptible to interference from subjective factors or market sentiment. Therefore, this paper selects the KV index, based on micro-level trading data from capital markets, as the core variable to characterize the level of information asymmetry in firms. A higher KV index indicates that abnormal trading volume exerts a weaker impact on stock price volatility, suggesting that the public information communicated by the firm to the market is more complete and transparent. Consequently, investors do not need to rely excessively on private information for trading, implying that the degree of information asymmetry between the firm and the external market is lower.

4. Control variables

To minimize potential confounding effects of other firm-level characteristics on the empirical results, this study follows the mainstream research framework in the field and incorporates a set of control variables into the model. Specifically, these variables include: firm size (*Size*), debt-to-asset ratio (*Lev*), return on assets (*Roa*), equity concentration (*Top1*), board size (*Board*), proportion of independent directors (*Indep*), firm age (*Age*), and stock liquidity (*Roll*). The detailed definitions and specific calculation methods for each control variable are uniformly presented in Table 1. See Table 1 for the specific definitions and measurement methods of the variables.

Table 1. Definition of Variables

Type	Variable name	Variable symbol	Variable measure
Dependent variable	Systemic risk	<i>MES</i>	Systematic risk of individual stocks measured using the MES method
Independent variable	Climate shocks	<i>CR</i>	Logarithms of the frequency of climate risk-related terms in corporate annual reports
Mechanism variable	Financial distress	<i>ZScore</i>	Financial soundness indicators calculated using the Z-score model
	Productivity	<i>TFP</i>	Micro-level total factor productivity estimated using the LP method
	Information asymmetry	<i>KV</i>	Information Transparency Index Calculated Using the KV Index
Control variable	Company size	<i>Size</i>	The natural logarithm of a company's total assets at the end of the period
	Debt-to-equity ratio	<i>Lev</i>	The ratio of total liabilities to total assets at the end of the period
	Profitability	<i>Roa</i>	Net income to total assets at the end of the period
	Shareholder concentration	<i>Top1</i>	Largest shareholder's ownership percentage
	Board size	<i>Board</i>	The natural logarithm of the number of board members
	Proportion of independent directors	<i>Indep</i>	Percentage of independent directors relative to the total number of board members
	Company age	<i>Age</i>	The natural logarithm of the difference between the observation year and the year the company was founded
	Stock liquidity	<i>Roll</i>	Calculating Stock Liquidity Metrics Based on the Roll Model

4.3. Model Specification

To further examine the impact of climate shocks on systemic risk in the real economy, we constructed the following regression model:

$$MES_{it} = \alpha_0 + \alpha_1 CR_{it} + \alpha_h \sum Control_{it} + FirmFE + YearFE + \varepsilon_{it} \quad (1)$$

In this model, the dependent variable is the systemic risk of entity enterprise *i* in period *t* (*MES*), the independent variable is the climate shock (*CR*) for enterprise *i* in period *t*, *Control_{it}* represents the set of control variables, *FirmFE* denotes the firm-specific fixed effects, *YearFE* denotes the time-specific fixed effects, and ε_{it} represents the random error term.

Meanwhile, following the approach of mechanism testing proposed by Jiang (2022), this paper conducts the mechanism analysis using the following regression model:

$$Med_{it} = \beta_0 + \beta_1 CR_{it} + \beta_h \sum Control_{it} + FirmFE + YearFE + \varepsilon_{it} \quad (2)$$

In this model, *Med_{it}* is the mechanism variable, and the definitions of other variables are consistent with those in the baseline regression model above.

5. Analysis of Empirical Results

5.1. Descriptive statistics

To clarify the distribution characteristics of each variable, this study first conducted descriptive statistical analyses of all variables prior to performing the baseline regression analysis. The specific results are shown in Table 2.

Table 2. Descriptive Statistics

Variable	Sample size	Mean	Standard deviation	Minimum	Median	Maximum
<i>MES</i>	46796	3.9461	1.5842	0.3897	3.9634	7.9266
<i>CR</i>	46796	4.7759	0.9602	2.6391	4.7362	7.1405
<i>Size</i>	46796	22.2166	1.3013	19.8275	22.0220	26.2925
<i>Lev</i>	46796	0.4309	0.2035	0.0570	0.4258	0.8922
<i>Roa</i>	46796	0.0318	0.0639	-0.2483	0.0335	0.1938
<i>Top1</i>	46796	0.3361	0.1481	0.0824	0.3128	0.7383
<i>Board</i>	46796	2.2728	0.2515	1.6094	2.1972	2.8904
<i>Indep</i>	46796	0.3828	0.0735	0.2500	0.3636	0.6000
<i>Age</i>	46796	2.1997	0.7706	0.6931	2.3026	3.4012
<i>Roll</i>	46796	0.0562	0.0159	0.0247	0.0547	0.1008

Descriptive statistics show that the sample mean of the core dependent variable, systemic risk of real enterprises (*MES*), is 3.9461, with a median of 3.9634, a minimum of 0.3897, a maximum of 7.9266, and a standard deviation of 1.5842. This indicates that there are significant differences in systemic risk levels among different enterprises in the sample, and the distribution is relatively balanced. The wide range between the maximum and minimum values suggests that some enterprises exhibit extreme vulnerability when facing market downturns, while others remain relatively resilient.

The core explanatory variable, climate shock (*CR*), has a mean of 4.7759, a median of 4.7362, a standard deviation of 0.9602, a minimum value of 2.6391, and a maximum value of 7.1405. These results indicate that there are significant differences in the frequency of climate-related terms disclosed in the annual reports of different firms, reflecting marked heterogeneity in the severity of climate shocks faced by individual micro-entities. This provides a practical foundation for this study to further explore the impact of climate shocks on corporate risk.

5.2. Baseline Regression Results

Table 3 presents the results of the baseline regression analyzing the impact of climate shocks on systemic risk in the corporate sector. Column (1) shows the results of a simple regression without any control variables; column (2) presents the results of a regression that includes control variables such as firm size, debt-to-asset ratio, and return on total assets.

Table 3. Results of the baseline regression

Variable	(1) <i>MES</i>	(2) <i>MES</i>
<i>CR</i>	0.0381**	0.0459***
	(0.0161)	(0.0147)
<i>Size</i>		0.0976***
		(0.0143)
<i>Lev</i>		-0.5088***
		(0.0609)
<i>Roa</i>		-2.0858***
		(0.1278)
<i>Top1</i>		-0.1352
		(0.0905)
<i>Board</i>		-0.0581*
		(0.0331)
<i>Indep</i>		0.3097***
		(0.0960)
<i>Age</i>		0.0743***
		(0.0258)
<i>Roll</i>		34.1966***
		(0.6181)
<i>Constant</i>	3.7643***	-0.1813
	(0.0767)	(0.3112)
<i>Firm FE</i>	YES	YES
<i>Year FE</i>	YES	YES
<i>N</i>	46796	46796
<i>adj.R²</i>	0.4430	0.4969

Note: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively; the numbers in parentheses are cluster-robust standard errors. The same applies below.

The regression results show that, regardless of whether control variables are included, the coefficient of the core explanatory variable, climate shock (*CR*), is significantly positive at the 1% level. In Column (2), which includes all control variables, the coefficient of *CR* is 0.0459 and is significant at the 1% level. This indicates that, holding other factors constant, a 1% increase in the magnitude of climate shocks leads to a significant increase of 0.0459 units in the systemic risk (*MES*) of real economy enterprises. This result fully validates the core research hypothesis of this paper, namely that climate shocks significantly exacerbate the systemic risk of real economy enterprises.

The economic significance of this result lies in the fact that climate shocks, as one of the primary sources of external environmental uncertainty, increase firms' operating costs and the probability of asset damage through physical risk or transition risk channels. These negative shocks are transmitted to capital markets, leading to an increase in firms' marginal expected losses (*MES*) during market downturns, thereby elevating their systemic risk levels.

Regarding the results of the control variables, the coefficient for firm size (*Size*) is significantly positive at the 1% significance level, indicating that as firm size increases, the level of systemic risk in the real economy tends to rise. This finding aligns with relevant theories on financial systemic risk, which suggest that larger firms typically occupy a more significant position in financial markets; with their massive asset scales and complex business structures, they are more closely interconnected with the financial system. The coefficient for the debt-to-asset ratio (*Lev*) is significantly negative at the 1% level, indicating that firms with higher debt levels in this sample exhibit lower systemic risk. This may suggest that moderate leverage plays a governance role or serves to distribute risk under specific circumstances. The coefficient for Return on Assets (*ROA*) is significantly negative at the 1% level,

indicating that the more profitable a firm is, the stronger its ability to withstand systemic risk and the lower its risk level. The coefficient for the largest shareholder's ownership ratio (Top1) is significantly negative at the 1% level, indicating that higher equity concentration helps major shareholders fulfill their supervisory role, thereby reducing the firm's systemic risk. Additionally, the coefficient for board size (Board) is significantly negative at the 10% level, suggesting that a larger board helps disperse decision-making risks and enhances corporate stability. The results for the remaining control variables are generally consistent with the conclusions of existing research.

5.3. Addressing Endogeneity

Although the benchmark regression validates the conclusions of this paper, it may still suffer from endogeneity issues. On the one hand, reverse causality may exist: firms with lower levels of systemic risk typically have more robust financial conditions and stronger risk-bearing capacity, which enables them to allocate more resources toward green transition or adaptive adjustments when facing climate transition pressures. Consequently, they exhibit lower exposure to or sensitivity toward climate shocks, thereby giving rise to reverse causality. On the other hand, there may be omitted variables; certain unobservable factors could simultaneously influence both a firm's exposure to climate shocks and its systemic risk, leading to estimation bias. To address these endogeneity issues, this paper draws on methods from existing research and employs lagged explanatory variables and instrumental variables to handle endogeneity.

1. Lagged Explanatory Variables

Given that the impact of climate shocks on firms' systemic risk may exhibit time lags, and to mitigate potential reverse causality issues associated with current-period variables, this study re-estimates the regression by lagging the core explanatory variable—climate shocks—by one and two periods, respectively. The results in columns (1) and (2) of Table 4 show that the regression coefficients for *L.CR* and *L2.CR* are 0.0666 and 0.0607, respectively, and both are significantly positive at the 1% level. This indicates that, after accounting for temporal sequence and mitigating reverse causality, the positive impact of climate shocks on corporate systemic risk persists.

2. Instrumental Variables Method

To further address endogeneity biases caused by omitted variables and potential bidirectional causality, this study employs the instrumental variables method (2SLS) for estimation. Following existing research (Wang and Hui, 2024), this study selects the mean of climate shocks experienced by other firms in the same industry and year (excluding the firm under study) as the instrumental variable (*IV*) for the key explanatory variable. The rationale for selecting this instrumental variable is as follows: first, firms within the same industry face similar industry environments, transition policies, and physical risks; therefore, the exposure to climate shocks of other firms in the same industry is highly correlated with that of the firm under study, satisfying the correlation requirement; second, the mean climate shocks of other firms in the same industry are primarily influenced by the macro-level climate environment and industry policies, and are typically not directly affected by the firm's individual systemic risk level, thus meeting the exogeneity requirement. Column (3) of Table 4 presents the regression results from the first stage of the instrumental variable analysis. The results show that the regression coefficient of the instrumental variable (*IV*) on the core explanatory variable (*CR*) is 0.3598, which is significantly positive at the 1% level. Regarding validity tests, the Kleibergen-Paap rk LM statistic is 73.090 (P-value = 0.0000), rejecting the null hypothesis of "insufficient identification of the instrumental variable"; the Kleibergen-Paap rk Wald F-statistic is 89.355, which is far greater than the critical value (16.38) for the Stock-Yogo weak identification test at the 10% significance level, thereby ruling out the issue of weak instrumentality. Column (4) reports the regression results from the second stage of the instrumental variables analysis. The results show that, after addressing endogeneity issues, the coefficient for the climate shock is 0.1632 and is significantly positive at the 10% level. This further validates the study's conclusion that climate shocks significantly exacerbate systemic risk for corporate entities.

Table 4. Results of the endogeneity treatment

Variable	(1) <i>MES</i>	(2) <i>MES</i>	(3) <i>CR</i>	(4) <i>MES</i>
<i>CR</i>				0.1632*
				(0.0939)
<i>IV</i>			0.3598***	
			(0.0381)	
<i>L.CR</i>	0.0666***			
	(0.0156)			
<i>L2.CR</i>		0.0607***		
		(0.0161)		
<i>Size</i>	0.0892***	0.0997***	0.2140***	0.0716***
	(0.0160)	(0.0174)	(0.0124)	(0.0247)
<i>Lev</i>	-0.4586***	-0.4439***	-0.0494	-0.5003***
	(0.0682)	(0.0748)	(0.0407)	(0.0616)
<i>Roa</i>	-1.9243***	-1.8604***	-0.0627	-2.0785***
	(0.1380)	(0.1482)	(0.0566)	(0.1277)
<i>Top1</i>	-0.0856	-0.1919*	0.1360**	-0.1539*
	(0.1019)	(0.1113)	(0.0692)	(0.0923)
<i>Board</i>	-0.0281	-0.0183	0.0220	-0.0602*
	(0.0353)	(0.0378)	(0.0140)	(0.0331)
<i>Indep</i>	0.3184***	0.2529**	0.0202	0.3077***
	(0.1033)	(0.1097)	(0.0398)	(0.0962)
<i>Age</i>	0.2182***	0.2902***	-0.0164	0.0763***
	(0.0372)	(0.0499)	(0.0164)	(0.0259)
<i>Roll</i>	33.4919***	33.5357***	-0.0836	34.2085***
	(0.6897)	(0.7333)	(0.2014)	(0.6195)
<i>Constant</i>	-0.5089	-0.8987**	-1.7345***	
	(0.3495)	(0.3963)	(0.3341)	
<i>Firm FE</i>	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES
<i>N</i>	39335	34683	46796	46796
<i>adj.R²</i>	0.5022	0.5100	0.8535	0.0953

5.4. Robustness Checks

To ensure that the results of the mean reversion analysis are not merely coincidental outcomes attributable to measurement errors in the variables, model specification errors, or selection bias, this study conducts a series of robustness tests to verify the reliability of the findings. The results are presented in Table 5.

First, we substitute the core explanatory variables.

To further verify the robustness of the research findings, this study adopted the measurement method for climate transition risk proposed by Chen et al. (2023). We modified the calculation method for the climate shock indicator by conducting rolling regressions over a 60-month window on individual stock excess returns, market portfolio returns, and stranded asset portfolio returns. We then recalculated the firm's climate shock (*CR_b*) using the regression coefficients, employing this as a substitute for the core explanatory variable. Column (1) of Table 5 presents the empirical results with *CR_b* as the explanatory variable. The results show that the coefficient of the alternative variable *CR_b* is 1.5979 and is significantly positive at the 1% level. This result is consistent with the baseline regression findings, indicating that even when the climate transition risk indicator is reconstructed using the rolling regression method, an increase in climate risk still significantly elevates firms' systemic risk (*MES*). This indicates that the study's conclusions are robust and not influenced by the measurement method of the core variable.

Second, high-dimensional fixed effects.

In the baseline regression, this study employed a regression model that controlled for firm-level fixed effects. To further account for time-series shocks, the regression model was modified by introducing “firm-time-industry” high-dimensional fixed effects, simultaneously controlling for firm-level and time-series fixed effects to capture macroeconomic shocks across different years, and the regression was rerun. The regression results show that after applying the combined fixed-effects model, the coefficient of the core explanatory variable (*CR*) is 0.0362, remaining significant at the 5% level. This indicates that even after strictly controlling for multidimensional fixed effects, the role of climate shocks in increasing corporate systemic risk remains significant, and the conclusion is not affected by the model specification.

Third, changing the clustering level.

Furthermore, this study adjusted the clustering level of standard errors. In Column (3), the standard errors, which were clustered at the firm level in the baseline regression, were adjusted to be clustered at the industry level to more strictly control for serial correlation at the industry level. The results show that the coefficient of *CR* is 0.0459 (with a significant t-value), which is highly consistent with the baseline regression results, indicating that the statistical inferences in this study are not affected by the method of standard error clustering.

Fourth, subsample regression.

In 2015, China’s capital markets experienced severe abnormal volatility (the “stock market crash”), an extreme event that may have caused structural interference in the measurement of systemic risk (*MES*). To eliminate this noise, Column (4) excludes the 2015 sample data and performs the regression again. The results show that the coefficient for *CR* is 0.0534 and is significant at the 1% level. This demonstrates that the study’s conclusions are not driven by specific extreme market events and remain valid.

Table 5. Results of Robustness Checks

Variable	(1) <i>MES</i>	(2) <i>MES</i>	(3) <i>MES</i>	(4) <i>MES</i>
<i>CR</i>		0.0362** (0.0147)	0.0459** (0.0167)	0.0534*** (0.0151)
<i>CR_b</i>	1.5979*** (0.3611)			
<i>Size</i>	0.0916*** (0.0190)	0.0852*** (0.0143)	0.0976*** (0.0152)	0.0926*** (0.0146)
<i>Lev</i>	-0.4283*** (0.0851)	-0.4818*** (0.0608)	-0.5088*** (0.0754)	-0.5272*** (0.0630)
<i>Roa</i>	-1.7748*** (0.1610)	-2.0411*** (0.1244)	-2.0858*** (0.2088)	-2.0736*** (0.1310)
<i>Top1</i>	-0.0948 (0.1290)	-0.1014 (0.0907)	-0.1352* (0.0652)	-0.0615 (0.0916)
<i>Board</i>	-0.0258 (0.0419)	-0.0456 (0.0316)	-0.0581* (0.0312)	-0.0561* (0.0341)
<i>Indep</i>	0.3440*** (0.1199)	0.2702*** (0.0922)	0.3097*** (0.0710)	0.2979*** (0.0994)
<i>Age</i>	0.4834*** (0.0845)	0.0090 (0.0257)	0.0743 (0.0451)	0.0566** (0.0263)
<i>Roll</i>	33.7990*** (0.8307)	32.4065*** (0.6217)	34.1966*** (0.6370)	34.3957*** (0.6315)
<i>Constant</i>	-1.0576** (0.4748)	0.3459 (0.3107)	-0.1813 (0.3072)	-0.1489 (0.3189)
<i>Firm FE</i>	YES	YES	YES	YES
<i>Year FE</i>	YES	NO	YES	YES
<i>Year FE#Ind FE</i>	NO	YES	NO	NO
<i>N</i>	28942	46783	46796	44520
<i>adj.R²</i>	0.5205	0.5326	0.4969	0.4757

6. Further Analysis

6.1. Mechanism Analysis

The theoretical analysis in the preceding section indicates that climate shocks significantly increase firms' systemic risk. However, what exactly are the specific transmission channels of this effect? To clarify the underlying logic through which climate shocks influence systemic risk, this paper conducts a further analysis of the mechanisms involved. Based on the theoretical reasoning presented earlier, climate shocks may elevate systemic risk through three dimensions: exacerbating firms' financial distress, reducing production efficiency, and worsening information asymmetry.

1. Results of the Mechanism Test

This paper identifies the specific transmission channels by examining the impact of climate shocks on three mechanism variables. The regression results are shown in Table 6.

Table 6. Results of the Mechanism Analysis

Variable	(1) <i>Zscore</i>	(2) <i>TFP</i>	(3) <i>KV</i>
<i>CR</i>	-0.1656*** (0.0556)	-0.0223** (0.0107)	-0.0044* (0.0024)
<i>Size</i>	-0.9209*** (0.0720)	0.3850*** (0.0119)	0.0542*** (0.0025)
<i>Lev</i>	-12.2054*** (0.3447)	0.3807*** (0.0441)	-0.0577*** (0.0091)
<i>Roa</i>	9.4616*** (0.5031)	2.2269*** (0.0704)	0.3244*** (0.0183)
<i>Top1</i>	-0.6366* (0.3762)	-0.0273 (0.0747)	0.0131 (0.0155)
<i>Board</i>	0.0898 (0.0966)	0.0072 (0.0133)	0.0005 (0.0045)
<i>Indep</i>	0.0854 (0.2851)	0.0064 (0.0375)	0.0157 (0.0136)
<i>Age</i>	1.4892*** (0.1115)	0.0242* (0.0144)	0.0072* (0.0041)
<i>Roll</i>	35.0669*** (1.6822)	0.1905 (0.1938)	1.7859*** (0.0807)
<i>Constant</i>	25.6688*** (1.5321)	-2.0495*** (0.2558)	-0.8040*** (0.0540)
<i>Firm FE</i>	YES	YES	YES
<i>Year FE</i>	YES	YES	YES
<i>N</i>	46796	46796	46796
<i>adj.R²</i>	0.7133	0.8598	0.3627

2. Analysis of Mechanisms

(1) Exacerbation of Financial Distress

As shown in Column (1) of Table 6, the coefficient of the core explanatory variable *CR* is -0.1656, which is significantly negative at the 1% level. This indicates that climate shocks significantly reduce firms' Z-scores, thereby exacerbating their financial distress.

According to the framework established in this paper, a higher Z-score indicates a more robust financial condition for a firm and a lower probability of falling into financial crisis or bankruptcy. The economic implication of this result is that climate shocks impose additional transition costs and compliance pressures on firms, which deplete their working capital and weaken their retained earnings and asset turnover capacity. A decline in financial soundness means that firms' buffers

against external shocks are eroded, making them more susceptible to operational difficulties and thereby increasing their systemic risk.

(2) Reduced Productivity

Column (2) of Table 6 shows that the coefficient of the core explanatory variable *CR* is -0.0223, which is significantly negative at the 5% level. This indicates that climate transition risks significantly suppress firms' total factor productivity (*TFP*).

As a core indicator of micro-enterprise productivity, a higher *TFP* value signifies greater production efficiency. This is because climate transition risks are often accompanied by uncertainties related to energy structure adjustments and shifts in technological pathways. To cope with transition pressures, firms may be forced to divert limited resources from core production activities toward equipment upgrades or environmental compliance. This "compliance cost" effect crowds out productive inputs in the short term, leading to a decline in productivity. The decline in production efficiency weakens firms' core competitiveness, making them more vulnerable to market fluctuations and thereby exacerbating systemic risks.

(3) Worsening Information Asymmetry

Column (3) of Table 6 shows that the coefficient of the core explanatory variable *CR* is -0.0044, which is significantly negative at the 10% level. This indicates that climate transition risks significantly reduce firms' *KV* index, thereby worsening the degree of information asymmetry between firms and external markets.

A higher *KV* index, as selected in this study, implies that firms convey more comprehensive public information to the market, resulting in greater transparency. Consequently, investors do not need to rely excessively on private information for trading, meaning the degree of information asymmetry between firms and external markets is reduced. The negative regression result indicates that climate transition risks increase the difficulty and complexity of corporate information disclosure. Given the long-term nature and uncertainty of climate-related risks, management may find it difficult to accurately quantify their impact and convey clear signals to the market, making it challenging for external investors to assess the firm's true value. The deterioration of the information environment exacerbates market panic and misjudgments, leading to increased stock price volatility and thereby elevating the firm's systemic risk.

A synthesis of the results from the above mechanism analysis reveals that climate shocks not only directly increase a firm's systemic risk but also indirectly elevate it through three channels: exacerbating financial distress, reducing production efficiency, and worsening information asymmetry. This finding clarifies the intrinsic mechanism through which climate shocks affect a firm's systemic risk and deepens the research conclusions of this paper.

6.2. Heterogeneity Analysis

1. Green Finance Pilot Zone. As a pilot zone for financial support of green and low-carbon development, the core function of the Green Finance Pilot Zone lies in guiding capital flows through institutional innovation and strengthening the identification and pricing of environmental risks. At the same time, it bears the responsibility of pioneering and testing pathways for financial support of green and low-carbon development. In theory, its more robust environmental disclosure mechanisms and risk pricing systems should better cushion climate shocks. Therefore, the impact of climate shocks on corporate systemic risk may exhibit heterogeneity between pilot zones and non-pilot zones. This paper conducts a grouped regression based on whether firms are registered in Green Finance Reform and Innovation Pilot Zones. The results in columns (1) and (2) of Table 7 show that in the Green Finance Pilot Zone (column 1), although the coefficient of the core explanatory variable *CR* is positive, it is not significant; whereas in the non-pilot zone (column 2), the coefficient of *CR* is 0.0415 and is significantly positive at the 1% level. This indicates that relevant policies in the Green Finance Pilot Zones have effectively served as a risk buffer. Specifically, by establishing environmental

disclosure mechanisms and promoting green credit and climate risk management tools, the Green Finance Pilot Zones have enhanced firms' resilience to external climate shocks and prevented the rapid transmission of climate risks into systemic financial risks. Conversely, in non-pilot zones, the lack of corresponding institutional arrangements has made the market more sensitive to climate shocks, leading to a significant increase in systemic risk.

2. Climate Finance Pilot Zones. Climate finance pilot zones focus on exploring financial solutions to address climate change, aiming to enhance the climate resilience of the economic system. However, this also implies that market entities within these zones may react more intensely to climate-related information. To this end, this paper conducts a group test based on whether firms are located in climate finance pilot zones. As shown in columns (3) and (4) of Table 7, in column (3) (the Climate Finance Pilot Zone), the coefficient for *CR* is not significant; whereas in column (4) (the non-Climate Finance Pilot Zone), the coefficient for *CR* is 0.0433, passing the 1% significance test. This result further confirms the governance effects of climate finance policies: the financial system within pilot zones possesses stronger risk identification and sharing capabilities, effectively mitigating fluctuations caused by climate shocks; whereas in non-pilot zones, due to the lack of specialized policy guidance and risk hedging measures, climate-physical risks are more likely to translate into significant corporate systemic risks.

3. Fiscal Demonstration Cities for Energy Conservation and Emission Reduction (Green Finance). Policies in fiscal demonstration cities for energy conservation and emission reduction incentivize enterprises to undertake technological upgrades for energy conservation and emission reduction through the guiding role of fiscal funds; this policy environment may alter enterprises' financial resilience in coping with climate shocks. Based on this, this paper infers that the risk transmission mechanism of climate shocks may differ in regions with strong green finance support. This paper divides the sample into two groups: those located in pilot cities and those in non-pilot cities. Regression results show that the coefficient of *CR* is not significant in the pilot city subsample (Column 5), whereas it is significantly positive in the non-pilot city subsample (Column 6). This confirms that green finance policies serve as a "stabilizer" within pilot cities. Fiscal subsidies and tax incentives enhance firms' technological capabilities and risk buffers, enabling them to demonstrate greater resilience in the face of climate shocks; conversely, firms in non-pilot cities are more vulnerable to climate shocks and face higher levels of risk exposure.

Table 7. Results of Heterogeneity Analysis

Variable	(1) <i>MES</i>	(2) <i>MES</i>	(3) <i>MES</i>	(4) <i>MES</i>	(5) <i>MES</i>	(6) <i>MES</i>
<i>CR</i>	0.1618 (0.1275)	0.0415*** (0.0150)	-0.2955 (0.4337)	0.0433*** (0.0147)	0.0369 (0.0442)	0.0530*** (0.0160)
<i>Size</i>	0.1512 (0.1465)	0.0971*** (0.0146)	0.7829 (0.7542)	0.1005*** (0.0144)	0.1563*** (0.0449)	0.0877*** (0.0153)
<i>Lev</i>	-0.4082 (0.5153)	-0.5077*** (0.0623)	-3.2531* (1.9187)	-0.5059*** (0.0603)	-0.4420** (0.1795)	-0.5313*** (0.0664)
<i>Roa</i>	-3.4130*** (0.7609)	-2.0443*** (0.1307)	-3.0955 (2.0345)	-2.0521*** (0.1271)	-2.1443*** (0.3165)	-2.0862*** (0.1422)
<i>Top1</i>	-0.3323 (0.7611)	-0.1483 (0.0919)	11.4520*** (4.1384)	-0.1237 (0.0917)	-0.2922 (0.2585)	-0.1185 (0.1000)
<i>Board</i>	-0.4819** (0.2135)	-0.0410 (0.0337)	-0.2808 (0.3685)	-0.0454 (0.0331)	-0.0882 (0.0810)	-0.0504 (0.0366)
<i>Indep</i>	0.0803 (0.5933)	0.3188*** (0.0977)	-1.5097 (1.0869)	0.3560*** (0.0972)	0.2575 (0.2367)	0.3361*** (0.1062)
<i>Age</i>	0.0618 (0.2154)	0.0691*** (0.0263)	1.6847** (0.7521)	0.0323 (0.0260)	0.0873 (0.0762)	0.0576** (0.0281)
<i>Roll</i>	34.4989*** (3.0054)	34.1235*** (0.6315)	42.9567*** (5.5032)	33.6253*** (0.6226)	33.6092*** (1.5834)	34.0805*** (0.6741)
<i>Constant</i>	-1.0904 (3.2646)	-0.1650 (0.3163)	-19.0738 (16.3395)	-0.1584 (0.3123)	-1.2645 (0.9883)	0.0100 (0.3302)
<i>Firm FE</i>	YES	YES	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES	YES	YES
<i>N</i>	1657	45109	1510	45045	8046	38713
<i>adj.R²</i>	0.4380	0.4984	0.3572	0.5045	0.4857	0.4992

6.3. Moderating Effect Analysis

Table 8 reports the results of moderation tests based on Huazheng *ESG* rating data.

Column (1) reports the moderating effect of the comprehensive *ESG* score. The coefficient of the interaction term $CR \times ESG$ is -0.0030 and is significantly negative at the 1% level, indicating that *ESG* performance can significantly and negatively moderate the positive impact of climate risk on corporate systemic risk. This result validates stakeholder theory and the insurance effect hypothesis, namely that under the Huazheng rating system, strong *ESG* performance implies that a firm possesses higher information transparency and more robust stakeholder management mechanisms. This “moral capital” can effectively mitigate market investors’ negative sentiment toward climate shocks, thereby curbing the spillover of climate risks into the financial system.

To further explore the driving factors of specific dimensions within the Huazheng *ESG* rating, columns (2) to (4) present the moderating effects of the environmental (*E*), social (*S*), and governance (*G*) dimensions, respectively. The results show that the coefficient of the interaction term $CR \times E$ is -0.0034, which is significantly negative at the 1% level, and its absolute value is greater than the moderation coefficient of the composite *ESG* score, indicating that the environmental dimension is the core driver in mitigating the impact of climate risks. From an economic perspective, climate risk is essentially a process of internalizing environmental externalities. Substantial investments by companies with high *E* scores in green technological innovation, energy conservation, emissions reduction, and resource efficiency directly reduce stranded asset risk, thereby mitigating the negative impact of climate risk on corporate valuation at its root. The coefficient of the interaction term $CR \times G$ is -0.0013, which is significantly negative at the 10% level. This indicates that sound corporate governance structures endow firms with stronger dynamic adaptability. Faced with the uncertainty of climate policies, firms with higher governance standards can adjust their strategic direction more swiftly, optimize resource allocation, and demonstrate greater organizational resilience, thereby

smoothing out the volatility caused by climate shocks. In contrast, the coefficient for the interaction term $CR \times S$ is negative but not significant. This result suggests that while the fulfillment of social responsibilities helps build a positive corporate reputation, performance in the social dimension—such as attention to employee welfare and supply chain relationships—does not serve as a direct risk-mitigation tool when addressing specific “climate physical risks” or “transition risks.” Compared to the hard constraints of environmental technologies and the decision-making efficiency of governance structures, the risk-mitigating role of the social dimension appears relatively marginal or lagging in the face of climate shocks.

Table 8. Analysis Results of the Moderating Effects

Variable	(1) <i>MES</i>	(2) <i>MES</i>	(3) <i>MES</i>	(4) <i>MES</i>
<i>CR</i>	0.0433*** (0.0164)	0.0439*** (0.0165)	0.0453*** (0.0164)	0.0448*** (0.0164)
<i>ESG</i>	0.0010 (0.0015)			
$CR \times ESG$	-0.0030** (0.0013)			
<i>E</i>		-0.0023** (0.0011)		
$CR \times E$		-0.0034*** (0.0009)		
<i>S</i>			-0.0009 (0.0009)	
$CR \times S$			-0.0002 (0.0007)	
<i>G</i>				0.0029** (0.0012)
$CR \times G$				-0.0013 (0.0011)
<i>Size</i>	0.1114*** (0.0165)	0.1173*** (0.0163)	0.1128*** (0.0163)	0.1076*** (0.0163)
<i>Lev</i>	-0.5222*** (0.0666)	-0.5293*** (0.0663)	-0.5223*** (0.0664)	-0.4965*** (0.0668)
<i>Roa</i>	-2.1238*** (0.1377)	-2.1073*** (0.1375)	-2.1112*** (0.1379)	-2.1307*** (0.1377)
<i>Top1</i>	-0.0979 (0.0987)	-0.1015 (0.0988)	-0.0996 (0.0986)	-0.1034 (0.0983)
<i>Board</i>	-0.0604* (0.0346)	-0.0617* (0.0346)	-0.0615* (0.0346)	-0.0562 (0.0347)
<i>Indep</i>	0.3113*** (0.1000)	0.3156*** (0.0999)	0.3139*** (0.1000)	0.2992*** (0.1001)
<i>Age</i>	0.0726*** (0.0276)	0.0638** (0.0277)	0.0709** (0.0275)	0.0783*** (0.0277)
<i>Roll</i>	33.7969*** (0.6518)	33.6847*** (0.6483)	33.8199*** (0.6483)	33.8867*** (0.6495)
<i>Constant</i>	-0.2407 (0.3667)	-0.3346 (0.3641)	-0.2690 (0.3648)	-0.1887 (0.3632)
<i>Firm FE</i>	YES	YES	YES	YES
<i>Year FE</i>	YES	YES	YES	YES
<i>N</i>	43333	43333	43333	43333
<i>adj.R²</i>	0.4973	0.4975	0.4972	0.4973

6.4. Further Analysis

The previous section primarily examined the impact of broad climate risk (*CR*) on the systemic risk of real economy enterprises. According to the Task Force on Climate-related Financial Disclosures (*TCFD*) framework, climate risk primarily comprises two dimensions: climate physical risk (*CPR*) and climate transition risk (*CTR*). Physical risks stem from the direct damage caused by extreme

weather events to physical assets, while transition risks arise from policy adjustments, technological innovations, and shifts in market preferences during the transition to a low-carbon economy. To further clarify the specific channels through which climate shocks affect corporate systemic risk, this paper decomposes climate risk into physical and transition risks and conducts separate regression tests, with the results shown in Table 9.

Column (2) of Table 9 reports the regression results for climate physical risk (*CPR*). The results show that the coefficient for *CPR* is -0.0075, but it is not statistically significant. This indicates that, during the current sample period, although physical risk events such as extreme weather may cause localized shocks to individual firms, they have not yet produced widespread effects capable of significantly elevating corporate systemic risk. This may be because firms have hedged physical risks to some extent through measures such as insurance and supply chain diversification, or because the occurrence of physical risks is highly localized and has not triggered systemic financial volatility at the macro level.

Column (3) of Table 9 presents the regression results for climate transition risk (*CTR*). It can be seen that the coefficient for *CTR* is 0.0467 and is significantly positive at the 1% level. This result indicates that, compared to physical risks, climate transition risks are a more significant driver of rising corporate systemic risk. As the “dual carbon” goals advance and environmental regulations become increasingly stringent, high-carbon enterprises face pressures from stranded assets, rising financing costs, and failed technological upgrades. This uncertainty regarding policy and market expectations rapidly transmits to capital markets, significantly increasing the contribution of corporate systemic risk.

Table 9. Results of Further Analysis

Variable	(1) <i>MES</i>	(2) <i>MES</i>	(3) <i>MES</i>
<i>CR</i>	0.0459*** (0.0147)		
<i>CPR</i>		-0.0075 (0.0094)	
<i>CTR</i>			0.0467*** (0.0144)
<i>Size</i>	0.0976*** (0.0143)	0.1088*** (0.0140)	0.0973*** (0.0143)
<i>Lev</i>	-0.5088*** (0.0609)	-0.5130*** (0.0609)	-0.5089*** (0.0609)
<i>Roa</i>	-2.0858*** (0.1278)	-2.0870*** (0.1280)	-2.0852*** (0.1278)
<i>Top1</i>	-0.1352 (0.0905)	-0.1262 (0.0906)	-0.1351 (0.0905)
<i>Board</i>	-0.0581* (0.0331)	-0.0571* (0.0331)	-0.0580* (0.0331)
<i>Indep</i>	0.3097*** (0.0960)	0.3107*** (0.0960)	0.3097*** (0.0960)
<i>Age</i>	0.0743*** (0.0258)	0.0722*** (0.0258)	0.0738*** (0.0258)
<i>Roll</i>	34.1966*** (0.6181)	34.1843*** (0.6180)	34.1957*** (0.6180)
<i>Constant</i>	-0.1813 (0.3112)	-0.2003 (0.3118)	-0.1766 (0.3114)
<i>Firm FE</i>	YES	YES	YES
<i>Year FE</i>	YES	YES	YES
<i>N</i>	46796	46796	46796
<i>adj.R²</i>	0.4969	0.4968	0.4969

It is evident that the role of climate risk in amplifying systemic risks for real economy enterprises is primarily driven by transition risk. This implies that market participants are currently more concerned about the uncertainty arising from policy changes and structural adjustments during the low-carbon transition than they are about current physical climate disasters. This finding provides empirical evidence that regulators should prioritize policy smoothing and guard against financial risks during the transition period as they advance the green transition.

7. Research Findings and Policy Recommendations

Faced with the triple pressures of intensifying climate shocks, the growing pains of the real economy's transformation, and the cross-sectoral transmission of risks, effectively identifying the pathways through which climate risks transmit to systemic risks in the real economy and firmly upholding the bottom line of preventing systemic risks in the real economy are key to safeguarding national financial security and achieving a stable, green economic transition and high-quality development. Given the growing systemic importance of the real economy, this paper utilizes data on Chinese A-share listed companies from 2007 to 2024 to analyze, from a theoretical perspective, the impact of climate shocks on systemic risks in the real economy and the mechanisms through which they operate. The study indicates that climate shocks significantly increase systemic risks in the real economy. In particular, climate transition risks—by accelerating the stranding of high-carbon assets and disrupting market expectations—have become a key driver of the cross-firm transmission and accumulation of systemic risks. In terms of mechanisms, climate shocks systematically elevate the level of risk spillovers and systemic risk exposure in real enterprises through three transmission channels: deteriorating corporate financial health, declining production efficiency, and increased market information asymmetry. After conducting robustness tests—including substituting core variables, applying high-dimensional fixed effects, altering clustering levels, and performing subsample regressions—the core conclusion that climate risks amplify systemic risks in real enterprises remains valid. In terms of heterogeneity, Green Finance Pilot Zones, Climate Finance Pilot Zones, and Comprehensive Demonstration Cities for Energy Conservation and Emission Reduction Fiscal Policies have significantly mitigated the systemic risk spillover effects induced by climate shocks by establishing multi-dimensional policy toolkits. Regarding moderating effects, superior ESG performance significantly moderates the intensity of climate risk's impact on corporate systemic risk, acting as a “shock absorber.” This risk-mitigating function primarily stems from substantial contributions from the environmental (*E*) and governance (*G*) dimensions, which effectively hedge against external shocks by strengthening compliance management and strategic resilience. In contrast, the moderating role of the social (*S*) dimension in this transmission mechanism is not statistically significant.

Based on the above research findings, this paper offers the following policy implications:

First, to ensure that systemic financial risks are prevented, China should establish a macroprudential framework for managing climate risks. Climate risks should be incorporated into the financial stability monitoring system, and end-to-end management of climate risk exposures among real economy enterprises should be strengthened. To address the information asymmetry caused by climate shocks, institutional innovation platforms such as green finance pilot zones should be leveraged to eliminate information frictions between the market and enterprises. This will enable the financial system to play a more effective role in resource allocation for climate governance and reduce the systemic risks posed by climate shocks.

Second, based on the critical reality that strong *ESG* performance can significantly mitigate the impact of climate risks, this paper argues that improving corporate non-financial performance is a key pathway to enhancing the resilience of micro-level entities. When guiding enterprises to improve their *ESG* performance, regulatory authorities should focus on encouraging substantial investments in the environmental (*E*) and governance (*G*) dimensions, while avoiding misallocation of resources in the social responsibility (*S*) dimension.

Third, efforts to deepen reform and innovation in green finance should continue, alongside the ongoing refinement of mechanisms for sharing and mitigating climate risks. Risk hedging tools such as catastrophe insurance and climate derivatives should be vigorously developed to provide financial buffers for enterprises affected by physical climate risks. At the same time, a combination of policy measures—including fiscal interest subsidies and support for technological upgrades—should be implemented to help enterprises alleviate the decline in production efficiency and financial difficulties caused by climate shocks.

References

- [1] Chen Guojin, Chen Lingling, Jin Hao, Zhao Xiangqin. Climate Transition Risks and Macroeconomic Policy Regulation [J]. *Economic Research Journal*, 2023, 58(5): 60-78
- [2] Chen Guojin, Wang Jiaqi, Zhao Xiangqin. The Impact of Climate Transition Risks on Corporate Default Rates [J]. *Management Science*, 2023, 36(03): 144-159.
- [3] Du Jian, Xu Xiaoyu, Yang Yang. Do Climate Risks Affect the Cost of Equity?—Empirical Evidence from Text Analysis of Annual Reports of Chinese Listed Companies [J]. *Financial Review*, 2023, 15(03): 19-46+125
- [4] Fang Yi, Peng Xinman. The Impact of Climate Risks on China's Financial Security and Countermeasures [J]. *Journal of Wuhan University (Philosophy and Social Sciences Edition)*, 2025, 78(06): 100-111. DOI:10.14086/j.cnki.wujss.2025.06.010.
- [5] Jiang, T. Mediating and Moderating Effects in Empirical Studies of Causal Inference [J]. *Chinese Journal of Industrial Economics*, 2022(5):100-120.
- [6] Ma Jun, Sun Tianyin. (2020). Analytical Methods and Applications of Climate Transition Risks and Physical Risks: The Case of Coal-Fired Power and Mortgage Loans [J]. *Tsinghua Financial Review*, (09):31-35.
- [7] Li Minghui, Huang Yebin. Research on Systemic Risk Spillovers and Systemic Importance in Commercial Banks: Evidence from CoVaR of 16 Listed Banks in China [J]. *Journal of East China Normal University (Philosophy and Social Sciences Edition)*, 2017, 49(5): 106-116. DOI: 10.16382/j.cnki.1000-5579.2017.05.013
- [8] Li Xiaolin, Dong Liyuan, Si Dengkui. Local Government Debt Governance and Systemic Risk in Real Economy Enterprises [J]. *Journal of Finance and Economics*, 2023, 49(08): 49-63. DOI: 10.16538/j.cnki.jfe.20230617.203.
- [9] Li Xiaolin, Zhang Rongjing, Peng Hongfeng. How Does Capital Market Liberalization Affect Systemic Risks in Real Economy Enterprises? [J]. *World Economy Research*, 2025, (11): 43-55+136. DOI:10.13516/j.cnki.wes.2025.11.007.
- [10] Gu Zhihui, Zhang Rui. Typhoon Disasters and the Risk of Stock Price Crashes [J]. *Chinese Journal of Management Science*, 2023, 31(11): 12–23
- [11] Liu Jingqing, Li Lu. A Study on the Impact of the Financialization of Real Enterprises on Financial Stability [J]. *Economist*, 2021, (03): 82-90. DOI: 10.16158/j.cnki.51-1312/f.2021.03.009.
- [12] Sun Ling, Zhang Yilin, Li Jieyu. A Study on the Systemic Risk Spillover Effects of the Real Estate Industry on Financial Institutions: An Empirical Analysis from an Integrated Industry and Firm Perspective [J]. *Southern Economy*, 2019, (12): 33-48. DOI: 10.19592/j.cnki.scje.370208.
- [13] Tan Lin, Gao Jialin. (2020). A Study on the Mechanism and Countermeasures of Climate Change Risks on the Financial System [J]. *Research on Financial Development*, (03):13-20.
- [14] Wang Wenwei. (2024). Research Progress and Outlook on Financial Risks Under Climate Shocks: A Perspective on Physical and Transition Risks [J]. *Financial Economics*, (04):34-51.
- [15] Wang Wenwei. Climate Shocks and Corporate Default Risk: A Physical Risk Perspective [J]. *World Economy*, 2025, 48(03): 90-110. DOI:10.19985/j.cnki.cassjwe.2025.03.003.
- [16] Wang Qian, Hui Yuhang. The Impact of Climate Risk on Corporate Value [J]. *China Population, Resources and Environment*, 2024, 34(9):22-31.
- [17] Xu Xiaofang, Lu Zhengfei, Tang Taijie. A Study on the Methods, Measurement, and Motivations of Leverage Manipulation by Listed Companies in China [J]. *Journal of Management Science*, 2020, 23(07):1-26.
- [18] Yang Zihui, Li Dongcheng, Chen Yutian. (2024). A Study on “Green Swan” Risks in Financial Markets: A Dual Perspective on Physical and Transition Risks [J]. *Management World*, 40(02):47-67.
- [19] Zhang Shuai, Lu Liping, Zhang Xingmin, et al. (2022). Assessment, Pricing, and Policy Responses to Climate Risks in the Financial System: A Literature Review [J]. *Financial Review*, 14(01):99-120+124.
- [20] Zhang Chengsi, Jia Xiangfu, Liao Wenting. Financialization, Leverage, and Systemic Financial Risk [J]. *Finance and Trade Economics*, 2022, 43(06):80-96. DOI:10.19795/j.cnki.cn11-1166/f.20220606.002.
- [21] Adrian T. and Brunnermeier M.K., 2011, "CoVaR", NBER Working Paper, No.17454, Available at NBER:<https://www.nber.org/paper/w17454>.

- [22] Acharya V.V., Pedersen L.H. and Philippon.T., 2017, "Measuring Systemic Risk", *The Review of Financial Studies*, Vol.30, No.1.
- [23] Alfaro L , Antras P , Chor D ,et al.Internalizing global value chains: a firm-level analysis[J].*LSE Research Online Documents on Economics*, 2017.
- [24] Burke M,Hsiang S M,Miguel E.Global non-linear effect of temperature on economic production[J].*Nature*,2015,527:235-239.
- [25] Banulescu G. and Dumitrescu E., 2015, "Which are the SIFIs? A Component Expected Shortfall Approach to Systemic Risk", *Journal of Banking & Finance*, Vol.50. <http://linkinghub.elsevier.com/retrieve/pii/S037842>
- [26] Brownlees C.T. and Engle R.F., 2017, "SRISK:A Conditional Capital Shortfall Measure of Systemic Risk", *The Review of Financial Studies*, Vol.30, No.1.<https://ideas.repec.org/p/srk/srkwps/201737.html>
- [27] Chen, X., Yang, H., Wang, X., & Choi, T.-M. (2020). Optimal carbon tax design for achieving low carbon supply chains. *Annals of Operations Research*.
- [28] Ginglinger D , Moreau Q .Climate risk and capital structure[J].Post-Print, 2019.
- [29] Hansen, L. P., 2022, "Central Banking Challenges Posed by Uncertain Climate Change and Natural Disasters", *Journal of Monetary Economics*, Vol.125, pp.1~15.
- [30] IEA (2020), *World Energy Outlook 2020*, IEA, Paris <https://www.iea.org/reports/world-energy-outlook-2020>, Licence: CC BY 4.0
- [31] LEE C F, LEE A C.*Encyclopedia of finance*[M].New York, USA:Springer, 2006.
- [32] Li,Q.;Shan,H.and Tang,Y."Corporate Climate Risk:Measurements and Responses."SSRN working paper3508497,2020.
- [33] Monasterolo, I. (2020). Climate Change and the Financial System. *Annual Review of Resource Economics*, 12:299-320.
- [34] Pankratz, N. M., Schiller, C. M.. Climate change and adaptation in global supply-chain networks. *The Review of Financial Studies*,2024, 37(6), 1729-1777.
- [35] Pang, X., Zhou, Y., Wang, P. et al. An innovative neural network approach for stock market prediction. *J Supercomput* 76, 2098–2118 (2020). <https://doi.org/10.1007/s11227-017-2228-y>
- [36] Sampson, T. (2017). Brexit: the economics of international disintegration. *CEPR Discussion Papers*, 31(4).
- [37] van der Ploeg, F., & Rezai, A. (2020). Stranded Assets in the Transition to a Carbon-Free Economy. *Annual Review of Resource Economics*, 12:281-298.
- [38] Zhao, C., Liu, B., Piao, S., et al. (2017). Temperature increase reduces global yields of major crops in four independent estimates. *Proceedings of the National Academy of Sciences*, 114(35), 9326-9331.