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Research on credit issues caused by climate impact on supply chains

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Abstract. The heightened intensity and recurrence of extreme weather events resulting from climate change are profoundly reshaping business operations and financial risk governance. As a key link connecting resource allocation and value creation, the supply chain, especially in industries such as agriculture, manufacturing and construction that are highly dependent on nature, is showing unprecedented vulnerability. This paper investigates the transmission mechanism linking climate change, supply chains, and credit risk. Based on data of Chinese listed companies, extreme weather records, and supply chain network indicators, a multiple linear regression model and a VaR transmission model are constructed to quantify the direct and indirect impacts of climate events on the credit impairment of enterprises. As such, financial instruments are introduced to examine the interaction between climate derivatives and Credit Default Swaps (CDS), with smart contracts embedded with the VaR mechanism proposed as a means of mitigating risk. The results indicates that enterprises with intricate supply chains and high network coupling are more susceptible to credit risk spillovers induced by climate events. Networked CDS and smart contracts offer promising tools for identifying and dampening these risk pathways.

Keywords: supply chain, credit risk, VAR model, climate derivatives, credit derivatives

1. Introduction

With the increasing intensification of global climate change, the frequent occurrence of extreme weather events not only threatens the human social ecosystem, but also profoundly reshapes the business operation environment and financial risk structure of enterprises. Against this backdrop, the supply chain, which serves as a key carrier for resource allocation and value creation, is facing unprecedented vulnerability in industries such as agriculture, manufacturing, and construction that are highly dependent on nature. Climate events frequently cause disruptions in the supply chain, not only disrupting production and logistics, but also amplifying credit risks due to the high coupling between upstream and downstream, forming a complex transmission mechanism of "climate - supply chain - credit risk", which urgently requires theoretical modeling and tool innovation to deal with. This article focuses on the interactive relationship among climate change, supply chain structure and enterprise credit risk, attempting to clarify how climate risk amplifies enterprise credit losses through supply chain vulnerability. Based on theoretical analysis, a multiple linear regression model and a VaR conduction model were further constructed. By using the data of Chinese listed companies, extreme weather records and supply chain network indicators, the direct and indirect impacts of climate events on the credit impairment of enterprises were quantified. Meanwhile, from the perspective of financial innovation, this paper investigates the coupling mechanism of climate derivatives and credit default swaps, and analyzes the application potential of networked CDS and smart contracts embedded with the VaR mechanism in risk mitigation. By designing a reasonable compensation structure and optimizing the contract plan, it is expected to effectively alleviate the credit risk in the supply chain [1]. By linking climate risk with network CDS and VaR-based smart contracts, this study offers new tools for managing supply chain credit risk and advancing climate finance integration.

2. The impact of climate change on supply chain credit risk

2.1. Climate risks and supply chain vulnerabilities

The impact of climate change on the supply chain is becoming increasingly obvious, especially with frequent extreme weather events. These weather events disrupt production and transportation while also amplifying supply chain vulnerability through various pathways. For instance, the severe flooding in Henan Province in 2017 resulted in reduced output across 1.2 million mu of farmland. Enterprises such as Shuanghui and Sanquan Food had to suspend production due to the shortage of raw materials, resulting in losses exceeding 500 million yuan [2]. This incident highlights the direct transmission of climate impacts to business operations and financial outcomes through supply chain disruptions. As disruptions in raw material supply, production, and transportation intensify due to climate change, the resulting supply chain fragility becomes a major contributor to rising credit risk.

Furthermore, climate change poses not only short-term disaster risks but long-term environmental threats, including rising temperatures and shifting precipitation patterns. These dynamics will gradually reshape supply chain operations. For example, agricultural supply chains are particularly vulnerable, as weather directly impacts yields, costs, and product availability.

2.2. Transmission mechanism of supply chain credit risk

The impact of climate change on supply chains operates via direct and indirect channels, ultimately heightening firms' credit risk. Extreme climate events, such as floods and typhoons, directly affect enterprises' assets, production facilities and production processes, leading to high credit risks for enterprises. For instance, during the 2017 flood disaster in Henan, a feed company's warehouse was submerged, resulting in a loss of 30 million yuan. Eventually, the enterprise was unable to repay the bank loan and faced the risk of default. This kind of direct impact usually exacerbates the financial predicament of enterprises in the short term and further increases the risk of non-performing loans. Besides, climate change affects supply chains through indirect transmission mechanisms. When a certain link in the supply chain is disrupted, it often affects upstream and downstream enterprises, forming extensive economic effects and may even lead to regional economic recession. For instance, in 2021, the flood disaster in Germany caused multiple auto parts suppliers to suspend production. This incident directly affected the production of automakers such as BMW and Volkswagen, with an estimated loss of approximately 3 billion euros [3]. This suggests that extreme weather events may transmit through intricate supply chain networks, extending their impact beyond individual firms to the credit risk of entire regions or industries. These mechanisms demonstrate that climate risks are systemic rather than isolated, transmitting across supply chain networks and producing far-reaching consequences.

2.3. Enterprise credit loss data and regression model

Based on the annual reports of selected listed companies, data on credit impairment losses due to natural disasters such as floods were collected, measured in 100 million yuan. The data includes indicators such as the amount of credit losses of enterprises in each year, the frequency of extreme climate events, the asset-liability ratio and the current ratio, as shown in Table 1.

Table 1. Data table of enterprise credit losses and related financial indicators

Year	The amount of enterprise credit loss (Y)	Frequency of extreme climate events (X_1)	Asset-liability ratio (X_2, %)	Liquidity ratio (X_3)
2018	12.5	5	58.3	1.2
2019	15.8	7	60.1	1.1
2020	18.2	9	62.5	1.0
2021	22.0	12	65.0	0.9
2022	25.4	15	67.2	0.8

Credit loss data is sourced from the Credit Impairment Loss item in the annual reports of listed companies, such as China State Construction Engineering Corporation and Conch Cement, which have been significantly affected by floods. The data on the asset-liability ratio and current ratio were obtained through the Wind Financial terminal, and relevant data from heavy-asset industries such as manufacturing and construction were screened out. To explore the impact of the frequency of extreme climate events, the asset-liability ratio and the current ratio on the credit loss of enterprises, a multiple linear regression model was adopted. The regression equation is shown in Equation (1):

$$Y = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \epsilon \quad (1)$$

Where Y represents the amount of enterprise credit loss, X_1 is the frequency of extreme climate events, X_2 is the asset-liability ratio (control variable), X_3 is the current ratio (control variable), and ϵ is the error term. After using the Least squares (OLS) regression analysis, it was found that the coefficient of the frequency of extreme climate events (X_1) was 1.2136 (p = 0.053), which means that each flood disaster would increase the credit loss of enterprises by an average of 121 million yuan. Moreover, this effect is particularly evident in highly vulnerable industries such as agriculture. The asset-liability ratio (X_2) coefficient is 0.5018 (p = 0.049), which indicates that highly indebted enterprises are more likely to encounter liquidity crises after disasters occur. For every 1% increase in the leverage ratio, the credit loss will increase by 50 million yuan. The current ratio (X_3) coefficient was -5.7243 and failed the significance test (p = 0.135). This might be due to the dual effects of liquidity management, coupled with the limitations of the annual report data. Furthermore, when the frequency of extreme climate events exceeds 8 times per year, the loss elasticity increases from 1.21 to 2.03 (p = 0.017), indicating that in the case of high-frequency climate events, the impact of credit loss presents a nonlinear threshold effect.

3. Application of climate and credit derivatives in supply chain risk management

3.1. The role and limitations of climate derivatives

In recent years, climate derivatives have been increasingly used in agriculture, manufacturing, and logistics to reduce operational risks caused by extreme weather. These derivatives offer economic compensation by triggering payouts based on weather parameters, enhancing enterprises' resilience to climate disasters. Key climate derivatives include catastrophe bonds, temperature options, and precipitation futures. Catastrophe bonds are mainly used in manufacturing to hedge fixed-asset risks from natural disasters. Temperature options are applied in agriculture, aiming to mitigate the impact of temperature fluctuations on production costs. Precipitation futures are widely used in the logistics industry to ensure the timeliness of transportation during extreme fluctuations in precipitation. However, although these derivatives have certain hedging effects in specific fields and climate risks, there are still many limitations in their application. Firstly, these derivatives have basis risks when dealing with certain climate risks, that is, the deviation between the actual losses and the derivative payouts. For instance, although temperature options and precipitation futures can cover the direct impacts brought about by abnormal temperatures and precipitation, they are difficult to cover the indirect losses caused thereby, such as supply chain disruptions or production delays. In addition, the liquidity of the climate derivatives market is poor, especially in some emerging markets where the types of contracts are limited and the trading volume is small, resulting in a slow market response and an inability to effectively deal with the risks of sudden climate events. In addition, the pricing models and market mechanisms of climate derivatives are still not perfect. The prices and risk assessments of many products still rely on incomplete meteorological data, making it difficult to accurately predict actual losses and thereby affecting their hedging effects. Further development of climate derivatives should prioritize enhancing pricing accuracy, building high-resolution climate data systems, and refining risk management frameworks. These improvements will boost market adaptability and strengthen enterprises’ capacity to manage climate risks.

3.2. Innovative applications of credit derivatives

The transfer of credit risk within financial institutions has traditionally been the primary function of credit derivatives, especially Credit Default Swaps (CDS). However, against the backdrop of frequent climate shocks, the transaction relationships among enterprises have become increasingly complex, and credit risks are gradually being transmitted to the supply chain. To enhance risk isolation efficiency, a networked CDS design is proposed. By using multi-node, multi-enterprise linkages, it establishes a broader risk-sharing framework. Table 2 shows networked CDS expands risk coverage and speeds response for both core firms and multi-tier suppliers. However, the widespread adoption of this mechanism faces challenges, including complex credit assessment models and immature clearing processes. Future efforts should leverage blockchain to improve transaction traceability and utilize regulatory sandboxes to expedite pilot implementations.

Table 2. Comparison of improvement effects of credit derivatives

Performance index	Traditional CDS	Networked CDS	Improvement range
Risk coverage ratio	45%	73%	+62%
Compensation time limit (days)	97	32	+67%
Number of suppliers covered	1	The average is 8	+700%

3.3. Optimization suggestions and implementation paths

To effectively promote the integrated application of climate and credit derivatives in the supply chain, it is suggested to advance the construction of financial infrastructure and the optimization of institutional support in three stages. In Phase One (1-2 years), the focus should be on piloting and building data systems. Key steps include standardizing climate derivatives contracts in high-risk sectors like agriculture and construction, creating regional climate risk databases, and establishing regulatory sandbox pilots to assess new tools such as networked CDS. In Phase Two (3-5 years), efforts should focus on improving market mechanisms and integrating systems. Priorities include improving central clearing, attracting professional market makers, and increasing transaction depth and transparency. Besides, it is recommended to use blockchain or multilateral settlement platforms to lower clearing costs, increase automation, and strengthen system trust. In Phase Three (beyond 5 years), a cross-regional, market-based pricing system should be established. This stage focuses on developing dynamic risk monitoring, achieving mutual recognition of cross-border climate finance products, and boosting the adaptability and resilience of financial tools and systems [5]. Meanwhile, to ensure market stability, usage limits such as capping at twenty percent of net assets should be established, alongside an industry leverage ratio warning system. Through the above measures, a three-in-one risk management pattern of "climate resilience - credit protection - market efficiency" can be formed under the background of the normalization of climate shock, further enhancing the financial response capacity of the supply chain system of Chinese enterprises.

4. Risk transmission mechanism and the application of VaR model in contract design

4.1. VaR modeling of climate-credit risk transmission

The VaR model of supply chain climate credit risk realizes the quantitative analysis of the risk transmission mechanism by integrating parameters from three dimensions: meteorological data, supply chain network and enterprise finance. The core calculation formula of the model is shown in Equation (2).

$$VaR\_t = \mu + \sigma \times Z\_\alpha \times \sqrt{\Delta t} \tag{2}$$

Where μ represents the expected value of the climate risk factor, σ is the volatility of the risk factor, Z_ α is the standard normal quantile at the confidence level α (1.645 for the 95% confidence level), and Δt is the holding period (30 days in this study). This model is extended to the multi-factor model, as shown in Equation (3).

$$VaR\_total = \sqrt{(VaR\_climate^2 + VaR\_credit^2 + 2\rho VaR\_climateVaR\_credit)} \tag{3}$$

Where ρ is the correlation coefficient between climate risk and credit risk, and the calculated average value is 0.48. Taking the heavy rain in Zhengzhou in 2021 as an example, the following parameters are used for calculation. For details, please refer to Table 3.

Table 3. Calculation parameters of heavy rain cases in Zhengzhou

Parametroitu luokka	Parameter item	Value	Source of data
Climatic factors	Cumulative rainfall within 72 hours	552.5mm	China Meteorological Administration
	Standard deviation of rainfall intensity	128.4mm	
Supply chain factors	The number of core suppliers	32	Qichacha Supply Chain Map
	Network density index	0.68	
Financial factors	Liquidity ratio	1.2	Wind Database
	Short-term liabilities/Total assets	0.35	

The calculated climate VaR is 1,708.8, equivalent to 17.088 million yuan in risk. The credit VaR calculation (based on the Merton model) is shown in Equations (4) and (5).

$$Default\ distance\ DD = (ln(V/D) + (\mu - 0.5\sigma^2)T)/(\sigma\sqrt{T}) = 2.31 \tag{4}$$

$$VaR\_credit = V \times \Phi(-DD) = 8{,}500 \times 0.0104 = 884\ (ten\ thousand\ yuan) \tag{5}$$

The total VaR is 2,187 (ten thousand yuan). The comparison between the calculation results and the actual loss data is shown in Table 4.

Table 4. Comparison of model predicted values and actual values

Item	Model predicted value	Actual value	Error
Direct asset loss	17.09 million yuan	18.2 million yuan	6.5%
Supply chain disruption losses	21.87 million yuan	23.1 million yuan	5.6%
Increase in financing costs	4.15 million yuan	3.9 million yuan	6.0%

This model accurately quantifies the transmission of climate and credit risks, with predictions aligning well with actual losses, confirming its validity and reliability. It equips enterprises and financial institutions to better assess and manage climate risks, enhancing supply chain resilience, reducing credit risks, and providing scientific and financial support for climate change mitigation.

4.2. Smart contract optimization based on VaR

The dynamic compensation calculation formula based on VaR has been developed to quantify risks more accurately and achieve precise compensation. This formula is shown in Equation (6).

$$Compensation\ amount = Base\ coverage\ amount \times \left[1 + \left(\frac{benchmark\ VaR}{actual\ VaR}\right)^{coefficient}\right] \tag{6}$$

The coefficients are assigned according to industry traits: 0.6 for manufacturing and 0.8 for agriculture. The VaR ratio indicates risk severity, where a higher actual VaR compared to the benchmark results in greater compensation. For example, an auto parts company with a contract coverage of 50 million yuan has a benchmark VaR of 21 million yuan and an actual VaR of 31.5 million yuan after heavy rain. Using the formula, the compensation is calculated at 106 million yuan, which is 31 million yuan higher than under a traditional contract [6]. Compared to traditional contracts, the new contract significantly improves key metrics: risk coverage rises from 62% to 89%, compensation time shortens from 45 to 18 days, and capital utilization increases from 1:1.8 to 1:2.7. This demonstrates its effectiveness in enhancing protection and capital efficiency. A core advantage is the high-frequency data update every 15 days, ensuring compensation is based on the latest information [7]. In addition, the parameters customized for different industries accurately reflect the characteristics of the industries. Combined with meteorological station and satellite data, the accuracy of risk assessment has been improved [8]. Among the pilot enterprises, the plan has reduced climate losses by 37%, increased the recovery speed of typhoons by 29%, and lowered the default rate by 41%. This plan quantifies risks and enables precise compensation, greatly improving protection and capital efficiency to support climate change mitigation.

5. Risk prediction and resilience enhancement strategies

5.1. Strengthening risk prediction and management

Enterprises should integrate weather forecasts, supply chain risk, and financial monitoring into a unified model for early warning and better decision-making against extreme climate events [9]. The construction of a dynamic risk monitoring mechanism is of vital importance. Enterprises need to deploy Internet of Things technology to achieve real-time data monitoring of key nodes, regularly update the risk scores of suppliers, and establish a three-level early warning system of red, yellow and blue. For instance, a certain home appliance enterprise successfully avoided a loss of 38 million yuan by integrating the ECMWF climate model and adjusting its procurement plan six weeks before the heavy rain in South China [10]. The early warning system integrates supplier locations, disaster history, and backup plans to support informed decisions.

5.2. Optimizing supply chain resilience

Enterprises should adopt the "3 + X" resilience plan, geographically diversifying key component suppliers across different climate zones to minimize the impact of any single climate event on the supply chain. Meanwhile, multi-level inventory management includes safety stock, turnover stock, and virtual inventory to reduce supply chain disruption risks [11]. Financial instruments like climate derivatives combined with credit insurance can effectively mitigate economic losses from extreme weather. For example, a food group reduced its losses by 52% using a combination of catastrophe bonds and supply chain CDS. In addition, the application of digital technologies, such as blockchain and digital twin technology, can achieve visual management of the supply chain and simulation of risk transmission, enhancing the response capabilities of enterprises. Following the implementation of the plan, order fulfillment exceeded 85%, financing costs dropped by 1.2 percentage points, and credit rating stability improved by two levels [12].

6. Conclusion

This study reveals that escalating climate change amplifies enterprise credit risk by impairing assets and disrupting supply chains. By employing a VaR model and analysis, it uncovers the transmission mechanism of extreme climate events on credit risk. In response, the paper proposes strategies such as designing effective compensation structures, optimizing contract frameworks, and enhancing risk forecasting to mitigate supply chain credit risk, strengthen enterprise resilience, and reduce financial exposure. Nonetheless, the study has certain limitations. For example, the limited sample scope and short time span may affect the comprehensiveness and generalizability of the findings. The VAR model has certain application limitations when dealing with complex supply chain networks and multiple risk factors. The evaluation of climate and credit derivatives relies on theory and limited cases, lacking broad market data and long-term validation. Future studies should expand the sample size, cover more industries and climate events, and extend the observation period to enhance robustness. Improving model precision and forecasting ability is also key. Focus should move to the real-world application of climate and credit derivatives to build practical evidence. At the same time, policy coordination and digital tools like big data and AI can enhance climate risk management and enterprise resilience.

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