

Dynamical Analysis of Multi-Layer Network Credit Risk Contagion of Banks and Enterprises in the CRT Market under Climate Risk Shocks

Xiaoyu Li^{1,2}, Hui An^{1,2}, Yanling Xia^{1,2}

¹School of Mathematics and Statistics, Guilin University of Technology, Guilin, China

²Guangxi Colleges and Universities Key Laboratory of Applied Statistics, Guilin, China

Email: 2120231913@glut.edu.cn

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Abstract

The behavior of banks and enterprises in the Credit Risk Transfer (CRT) market determines the diffusion and contagion of credit risk. Research on its contagion evolution mechanism will contribute to establishing financial regulatory strategies. This paper adopts the complex network analysis method and innovatively introduces climate risk influencing factors to explore the credit risk contagion mechanism between banks and enterprises. Based on the susceptible-infected-recovered-susceptible (SIRS) model, a credit risk contagion evolution model is constructed for bank-corporate networks which considers key factors such as risk resistance, capital adequacy, climate change shocks, and climate transition risk. First, the credit risk contagion mechanism between banks and enterprises and the impact of complex network heterogeneity on risk diffusion are analyzed at the theoretical level. On this basis, the advantages of the SIRS model in the study of risk contagion in the CRT market are explored. Subsequently, the evolutionary characteristics of credit risk contagion between bank-corporate credit networks are analyzed using simulation methods. The research results show that: In the bank credit network, the probability of credit risk contagion shows a marginally decreasing characteristic as risk resistance and capital adequacy increase. However, it increases with the probability of credit risk contagion from enterprises to banks and the impacts of climate change. In the enterprise credit network, the probability of credit risk contagion shows a marginally decreasing trend with improvements in information disclosure and market liquidity. However, it increases with climate transition risks and the contagion of credit risk from banks to enterprises, showing a marginally increasing upward trend. The high heterogeneity of the BA scale-free network significantly amplifies the credit risk contagion effects between banks and enterprises, while the relative homogeneity of the WS

small-world network can, to some extent, mitigate the concentration of credit risk contagion.

Keywords

Complex Networks, SIRS Model, Credit Risk Contagion, Climate Risk, Bank-Corporate Credit Network

1. Introduction

In recent years, there has been growing interest in studying financial interconnectedness. Various financial crises and defaults by banks and enterprises have exposed the vulnerabilities and complexities of the financial system, highlighting the importance of understanding how risks propagate in the market. Credit risk is caused by the uncertainty in the financial conditions of specific counterparties, referring to the risk of loss arising from a borrower's inability to repay debt. Credit risk transfer (CRT) can lead to mutual contagion between two industries, increasing the risk of a crisis. Allen *et al.* suggested that in the CRT market, certain entities, such as banks and enterprises, may face difficulties in fulfilling their external debt obligations when impacted by exogenous shocks (such as economic fluctuations, market volatility, or interest rate changes) [1]. This not only directly threatens the financial health of individual institutions but may also trigger a broader credit risk contagion effect. In such cases, the credit risk transfer mechanisms in the CRT market (such as asset securitization and credit derivatives) play a crucial role. By diversifying and transferring risks, these mechanisms help financial institutions avoid potential credit crises.

Credit risk contagion primarily manifests when a financial institution or enterprise is unable to meet its debt obligations, which may lead other entities with debt relations to face financial difficulties, forming a default chain. This contagion effect means that a single default event can trigger a broader credit crisis [2]. During the process of credit risk contagion, when financial institutions face default risks and liquidity is insufficient, market liquidity can tighten. A liquidity crisis can pull more banks and enterprises into financial trouble, resulting in a wider spread of credit risk contagion [3]. In a globalized financial system, credit risk is not only transmitted between banks but can also cross different markets. For example, a crisis in one country's banking system may spread to financial markets in other countries or regions [4]. Banks, as intermediaries for the flow of funds, are closely linked to enterprises through financial transactions. The bankruptcy of an enterprise may lead to severe liquidity shocks for the banks connected to it through debt relations. These interconnected relationships can trigger a "domino effect" of defaults between banks and enterprises. The 2008 subprime mortgage crisis and the 2010 European debt crisis are typical examples. In the modern financial system, banks and enterprises, as core nodes in the system and primary channels for sys-

temic risk contagion, have a significant practical role in the transmission of credit risk. The debtor-creditor relationship, acting as an edge in the network, represents the credit risk contagion between banks and enterprises, which is particularly important in a two-layer network structure. Their mutual connections and credit risk contagion not only affect their own stability but also have a direct impact on the overall health and security of the entire financial market. Since enterprises primarily rely on loans from financial institutions for external financing, and financial institutions' funding sources and usage are heavily concentrated in enterprises, the risk interdependence between banks and enterprises strengthens during economic downturns. Easy access to financing can boost investment in projects; however, if enterprises mismanage funds and expand blindly, it is likely to lead to stock market bubbles and their subsequent collapse. Bernanke and others summarized the principle of the financial accelerator, which refers to the contraction of investment caused by rising external financing costs during economic recessions, thereby triggering a new round of adverse effects. This amplification effect is known as the "financial accelerator principle [5]-[7]."

To accurately capture the complexities of modern financial systems, it is essential to explicitly delineate the Credit Risk Transfer (CRT) market within our network framework. The CRT market refers to the ecosystem of financial mechanisms—such as credit default swaps (CDS), collateralized debt obligations (CDOs), asset-backed securitization, and loan syndication—that allow institutions to unbundle and reallocate credit exposure without necessarily transferring the underlying assets. In the context of our two-layer network model, it is crucial to distinguish these CRT business channels from traditional commercial credit relationships. While general credit links represent standard, direct financing (e.g., standard bank loans to non-financial enterprises), the CRT channels are modeled as specialized, often hidden, directed edges. Specifically, in this paper, intra-layer interbank links (representing banks hedging or offloading risks among themselves) and targeted inter-layer links connecting banks to specific financial enterprises (such as shadow banks, hedge funds, or special purpose vehicles that absorb securitized risks) represent the CRT channels. By isolating these CRT edges from standard loan linkages, this model provides a more precise institutional setting, allowing us to capture how mechanisms originally designed for risk mitigation can paradoxically act as high-speed conduits for systemic contagion during severe climate or economic shocks.

Current academic research on credit risk contagion between banks and enterprises mainly focuses on the following aspects. First, empirical studies on the structural characteristics of the credit network between banks and enterprises. Georg *et al.* by comparing different inter-bank network structures, demonstrated that, compared to random networks, monetary center networks exhibit higher stability [8]. Some scholars have constructed a multi-agent credit network model between banks and enterprises, describing the credit relationships among banks, enterprises, and the interactions between them. The study found that the asset

distribution of banks follows a normal distribution, while the tail distribution of enterprise assets follows a power-law distribution. The network between banks and enterprises typically exhibits scale-free characteristics and community structures, with centrality measures widely used in both bank and enterprise networks [9] [10]. Secondly, based on a complex network perspective, research has examined systemic risks between banks and enterprises. Systemic risk in the financial system mainly arises from the intricate relationships between financial institutions, such as loans between banks and enterprises. Due to the multiple contagion pathways within the financial network, involving various financial entities, a multi-layer framework can be more effective in describing these interdependent relationships. The risk value, scale, debt, and trade credit of enterprises are correlated with two dimensions of systemic risk [11]. As banks are highly irreplaceable within the economic and financial system, a significant positive correlation exists between the size of financial institutions and systemic risk. An increase in bank size leads to an increase in systemic risk, while an increase in bank capital mitigates systemic risk. Finally, theoretical analyses have examined the influence mechanisms and evolution characteristics of factors such as regulatory rescue strategies on credit risk contagion in bank-enterprise networks [12]. Cheng *et al.* studied the impact of financial technology on credit risk, arguing that bank financial technology significantly reduces the credit risk of Chinese commercial banks. Moreover, large banks, state-owned banks, and listed banks have relatively weaker negative effects on credit risk [13]. Qian *et al.* proposed internal strategies for controlling risk contagion in enterprise networks based on existing external strategies, analyzing the impact of these strategies on credit risk contagion within networks [14]. Erlend Nier *et al.* analyzed the influence of capital adequacy, bank interconnections, the scale of inter-bank risk exposures, and the degree of system concentration on bank chain defaults. J.L. Ma *et al.* demonstrated that liquidity shortages are a key factor triggering risk contagion and that higher leverage results in greater losses for creditors [15]. Rishehchi *et al.* pointed out that the complexity of business partner networks is a key factor influencing the variability of contagion-induced losses [16].

Although existing studies have explored the structural characteristics of bank-enterprise credit networks, systemic risk from a complex network perspective, and related factors such as regulatory rescue, as well as the role of various economic and financial factors in credit risk contagion, little attention has been given to the influence of climate change, especially climate transition risks (CTR), on credit risk contagion between banks and enterprises [17]. Weather factors can be linked to the credit conditions of banks and enterprises through various channels. The transition to a low-carbon economy to mitigate the adverse impacts of climate change brings about cash flow risks known as climate transition risks (CTR), which may impair the debt repayment capacity of enterprises and increase credit risk in enterprise networks [18]. Over the past decade, climate change has impacted financial markets and undermined financial stability. Risks triggered by

climate change (e.g., global warming) affect the economic development of entities, which in turn affects the stability of financial markets [19]. Recently, with the increasing urgency of global climate risks, financial institutions are also facing growing climate risks. Effectively quantifying and assessing climate-related financial risks is critical for financial institutions to establish risk management mechanisms.

Using complex network theory to study the characteristics of credit risk contagion has been proven effective. Moreover, complex network-based epidemic models, originally used to describe the spread of infectious diseases, can also be applied to describe interactions between individuals from a micro perspective. These models have been widely applied in fields such as financial risk contagion, social behavior diffusion, and information dissemination. May *et al.* observed that the environment, targets, and mechanisms of diffusion between enterprises are strikingly similar to those in epidemic models. They suggested that epidemic models could be used to analyze financial risk contagion [20]. Huang *et al.* applied the SIR (Susceptible-Infected-Recovered) model to analyze the contagion of financial shocks [21]. Wang *et al.* used epidemic models to analyze the impact of information disclosure strategies on credit risk contagion between counterparties [22]. Therefore, the SIRS (Susceptible-Infected-Recovered-Susceptible) model can be used to describe the process of credit risk contagion in bank-enterprise credit networks.

In summary, this paper suggests that credit risk spreads through the bank-enterprise network formed by credit relationships. Based on an epidemic model and considering the contagion mechanism and influencing factors of credit risk between banks and enterprises, a two-layer network model for credit risk contagion between banks and enterprises is constructed. The paper analyzes the evolution characteristics of credit risk contagion between banks and enterprises. The main contributions of this paper are as follows:

- 1) A two-layer network is constructed to describe the credit network structure formed by banks and enterprises.
- 2) The impact of climate change on credit risk contagion is considered, with climate change shocks taken as one of the factors influencing bank credit risk and climate transition risk (CTR) as one of the factors influencing enterprise credit risk.
- 3) In-depth analysis of the credit risk contagion in the inter-bank credit network, considering factors such as capital adequacy, climate change impacts, risk resistance, inter-bank credit contagion levels, and network structural heterogeneity; in the inter-enterprise credit network, factors such as information disclosure coefficients, climate transition risks (CTR), market liquidity of enterprise assets, inter-enterprise credit contagion levels, and network structural heterogeneity; and the credit risk contagion levels between the bank and enterprise networks.

The remainder of the paper is organized as follows: Section 2 analyzes the credit risk contagion mechanism between banks and enterprises in the two-layer network framework. Section 3 considers the influencing factors of credit risk conta-

gion between banks and enterprises and constructs a theoretical model for credit risk contagion for further analysis.

Section 4 provides an in-depth analysis of the impact of various parameters on risk contagion in the bank-enterprise two-layer network model through numerical simulations. Section 5 offers a comprehensive summary and discussion of the findings.

2. Credit Risk Contagion Analysis of Banks and Enterprises in CRT Market Based on SIRS Modeling

2.1. Contagion Mechanism and Model Selection

In the CRT market, credit risk contagion between banks and enterprises refers to the process in which risk is transmitted between banks and enterprises through credit links, triggered by both internal and external disturbances. During this process, contagion between banks and enterprises is bidirectional. As the decision-making behavior and operational performance of enterprises are easily influenced by various uncertain factors such as economic conditions, social changes, and policies, the formation of enterprise credit defaults often exhibits characteristics of concealment, suddenness, and strong contagion. Once an enterprise defaults, this default behavior can rapidly spread through the credit relationship between the enterprise and the bank, resulting in credit losses for the bank. Further, this credit loss may propagate through the inter-bank credit network to other banks, leading to broader financial instability. Similarly, a bank's default can quickly spread to enterprises through the credit relationship between the bank and enterprise, causing credit losses for enterprises.

In the bank network, factors such as balance sheet links, jointly held assets, and inter-bank lending relationships form key interconnections between banks of different sizes. Under normal conditions, these interconnections help improve the liquidity and stability of the financial system. However, when facing credit risk contagion, these connections can exacerbate the spread of risk. Initially, some banks may default due to deteriorating asset quality and credit losses, becoming the origin of credit risk contagion in the network. This default propagates quickly through inter-bank relationships and transactions, affecting the financial health of other banks. Banks in the network can be divided into three categories.

Susceptible Banks: These banks have strong financial health and low-risk exposure. Although their own credit risk is low, their high connectivity with other banks makes them vulnerable to the defaults of other banks, thus exhibiting higher correlated credit risk.

Defaulted Banks: Due to internal management issues or external economic deterioration, these banks default. They are important nodes for credit risk contagion in the network because, in addition to facing their own credit issues, they are likely to transmit risk to other banks.

Immune Banks: These banks typically have strong capital reserves, good asset quality, and sound operational conditions, which allow them to better withstand

external shocks and internal risks. They are less affected by contagion and play an important buffering and stabilizing role in the network. However, due to changes in market conditions, an immune state can potentially revert to a susceptible state.

In the enterprise network, some enterprises may eventually default due to factors such as the sharp deterioration of the external economic environment, broken supply chains, decreased market demand, and financing difficulties. In this network, credit risk contagion occurs through financial product transactions between enterprises. Considering the level of credit risk and the ability of enterprises to resist such risks, we can classify enterprises in the CRT market into three states.

Susceptible Enterprises: These enterprises have low-risk exposure, sound financial conditions, and strong risk management capabilities.

Defaulted Enterprises: These enterprises are unable to meet their debt obligations and often face serious financial difficulties and operational issues. Influenced by both internal and external factors, they default and may spread this risk to other enterprise nodes.

Immune Enterprises: These enterprises possess strong capital reserves, flexible financing channels, and robust risk control mechanisms, enabling them to effectively withstand market fluctuations and credit risk shocks. They are typically industry leaders.

In the bank-enterprise credit network, when the losses suffered by banks are small and credit risk transmission remains within controllable limits, the contagion effect typically remains below the critical threshold, and banks generally do not retract loans from enterprises. However, if the contagion shock exceeds the bank's risk tolerance threshold, the bank may choose to withdraw loans from the enterprise. This withdrawal of funds exacerbates the enterprise's financial distress and may lead to more severe credit risk contagion.

The SIRS (Susceptible-Infected-Recovered-Susceptible) model, traditionally used to describe the dynamics of infectious diseases, is applied in this paper to model the spread of credit risk through the network. The SIRS model divides the population into three categories: susceptible individuals, infected individuals, and recovered individuals, where recovered individuals have temporary immunity and return to the susceptible state after a period of time. When susceptible individuals come into contact with infected individuals, they become infectious and transition to the infected state. Infected individuals can be treated and may recover, returning to the susceptible state after immunity wears off.

The SIRS framework is uniquely suited for this study as it captures the cyclical and persistent nature of financial crises, which traditional linear or permanent-recovery models (such as SIR) fail to address. In the context of the CRT market, the "Recovered/Immune" state (R) represents an economic phase where a bank or enterprise has undergone successful debt restructuring, received a liquidity injection from a lender of last resort, or executed an emergency capital increase. This state grants the entity a "temporary financial buffer" or "reconstructed cre-

ditworthiness.” However, this immunity is inherently transient; the transition from R back to S (SIRS’s defining feature) accurately reflects the “re-default” phenomenon. In an environment of ongoing climate volatility or structural economic shifts, the effectiveness of once-successful rescue measures may diminish as capital reserves are depleted or asset values face renewed downward pressure. Thus, the SIRS model aligns perfectly with the reality that financial recovery does not equate to permanent safety, allowing this study to simulate the “recurring waves” of credit contagion often observed in complex bank-enterprise networks.

In summary, based on the theory of SIR contagion model, this paper combines the characteristics of the CRT market and the credit relationship between the bank-enterprise network to construct the SIRS-SIRS model of credit risk contagion in bank-enterprise association, in order to portray the credit risk contagion mechanism between the bank network and the enterprise network. In the CRT market, most of the bank’s credit originates from non-performing loans, and the loans provide a channel for enterprises to shift their risks to the bank. Under the credit system, firms conduct their production operations through borrowing and transmit risk to banks through debt and financing. In addition, the cross-linkages between enterprises enhance the vulnerability of their solvency, once an enterprise defaults, the credit risk will be contagious and spread within the enterprise network, and through the credit linkages between banks and enterprises, it will be contagious to some of the banks, which will lead to non-performing loans, and may lead to a banking crisis, accelerating the contagion of credit risk in the banking network. When the bank credit loss reaches a certain threshold, the bank in order to reduce its own formation of default risk, may take tightening credit policy, the risk of contagion to the relevant enterprises, expanding the impact of the initial shock, and thus the formation of credit risk contagion network between banks and enterprises.

The credit risk contagion path of bank-enterprise association is shown in **Figure 1**.

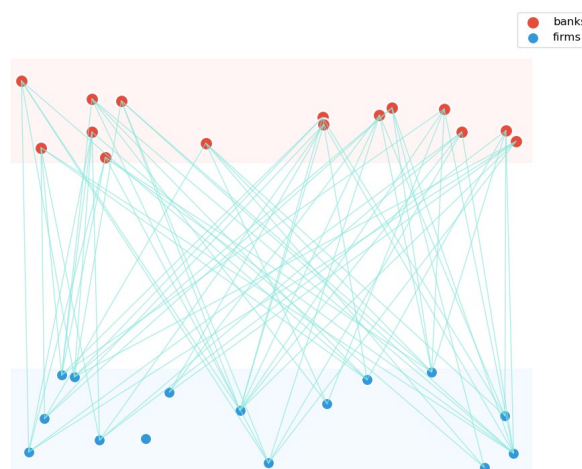


Figure 1. Credit risk contagion path in the bank-enterprise linked network.

2.2. Assumptions on Variables and Parameters

Consider the contagion process of a two-layer correlated heterogeneous network, where nodes represent banks or firms and edges represent financial relationships (e.g., loans). In this paper, we set the number of nodes of the bank network and the firm network as M and N , respectively, which have different connectivity. Networks $AB(BA)$, both of size $M + N$, represent inter-layer connections from layer $A(B)$ to layer $B(A)$. Layer $A(B)$ node characteristics are represented by the average degree $\langle k_a \rangle (\langle k_b \rangle)$, $\langle k_{ab} \rangle$ denoting the average interlayer connection of A layer nodes and B layer nodes, and the infection scores of A layer nodes and B layer nodes are represented by $\rho_A(t)$ and $\rho_B(t)$, respectively, and the interlayer connections are randomly correlated between the two layers, to construct the risk contagion model based on the bank and corporate credit network, and the SIRS model of the two-layer network is schematized as follows (Figure 2).

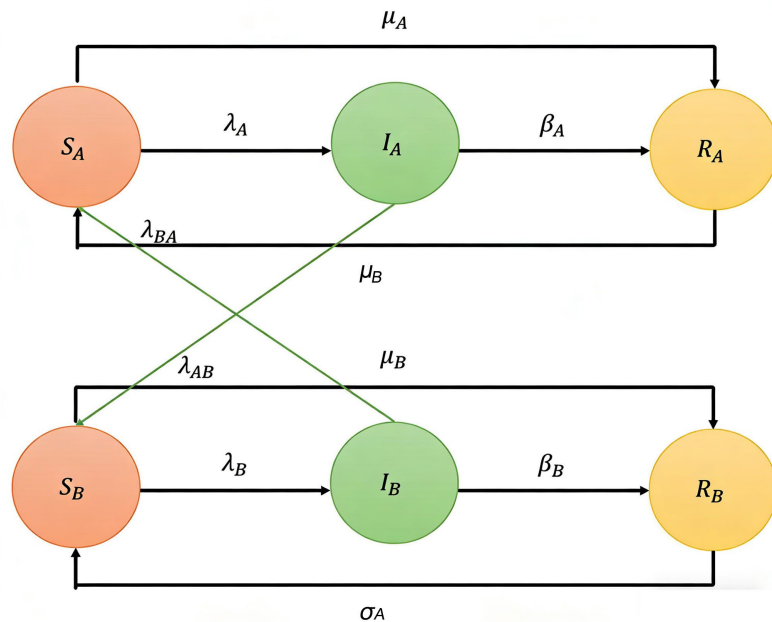


Figure 2. Two-layer network SIRS model.

Susceptible banks S_A can be transformed into defaulted banks I_A through extensive default risk arising from internal and external factors such as capital shortages and loan defaults. Defaulted banks I_A can be transformed into immune banks R_A through restructuring, capital injection and the introduction of external investors to effectively protect themselves from credit default risk. However, immune banks R_A can also be transformed back into susceptible banks S_A in the face of persistent market volatility or economic pressures. However, in the face of persistent market volatility or economic stress, an immune bank may also be transformed back into a susceptible bank. This transformation process can be regulated by different financial policies. For example, governments and regu-

lators can adopt policies such as capital injection, loan reserves, and liquidity support to help default status banks tide over the crisis. After banks return to an immune state, regulatory policies can implement risk monitoring and early warning mechanisms to ensure that banks maintain sufficient capital adequacy and risk resistance to avoid falling back into a susceptible state. In addition, reforms and innovations in the financial market, such as improving transparency, strengthening regulation and developing the credit derivatives market, can also be effective in enhancing the immunity of banks and reducing the contagion of credit risk.

Based on the above analysis, we make the following assumptions:

Assumption 1: At the initial time point, some bank nodes, due to deteriorating asset quality, credit losses, market fluctuations, economic recession, regulatory policy changes, and liquidity tightening, may experience credit defaults or increased credit risk. These banks may, with probability λ_A ($0 < \lambda_A < 1$) transmit the risk through lending relationships to other banks with which they have lending ties, causing them to transition into default banks. Additionally, susceptible state banks S_A can through timely identification and elimination of non-performing loans or assets, reduce the bad debt on their capital, thereby improving their capital adequacy ratio, and with probability μ_A , transition into immune state banks R_A . Default state banks I_A can resist credit default risks through restructuring, capital injection, and the introduction of new investors, and with probability β_A , transition into immune state banks. Immune state banks R_A , however, may also, due to external shocks or market changes, transition back into susceptible state banks S_A with probability α_A .

Assumption 2: At the initial time point, some enterprise nodes, due to internal and external shocks, financial crises, market environment fluctuations, and other factors, may experience credit defaults or increased credit risk. These enterprises may, with probability λ_B ($0 < \lambda_B < 1$), transmit the risk through cross-shareholding relationships to related enterprises, causing them to transition into default enterprises. Additionally, susceptible state enterprises S_B can, by strengthening their capital base, optimizing their business structure, improving operational efficiency, and enhancing risk management, with probability μ_B , transition into immune state enterprises. Default state enterprises I_B can resist credit default risks through restructuring, capital injection, and the introduction of new investors, and with probability β_B , transition into immune state enterprises R_B . Immune state enterprises R_B , when facing various economic, market, and policy shocks, may also, with probability α_B , transition back into susceptible state enterprises S_B .

Assumption 3: In the CRT market, the default state nodes in the enterprise credit network I_B are connected to the susceptible state nodes in the bank network S_A . Additionally, the default state nodes in the enterprise credit network I_B will, with probability λ_{BA} ($0 < \lambda_{BA} < 1$), transmit credit risk to the susceptible state nodes in the bank network S_A , thereby accelerating the risk of their default. Similarly, the default state nodes in the bank credit network I_A are connected

to the susceptible state nodes in the enterprise network S_B . Furthermore, the default state nodes in the bank credit network I_A will, with probability λ_{AB} ($0 < \lambda_{AB} < 1$), transmit credit risk to the susceptible state nodes in the enterprise network S_B , thereby accelerating the risk of their default.

The parameters of the assumed model are shown in **Table 1** below:

Table 1. Parameters of the model.

Parameters	Description
$S_{A(B)}(t)$	At time t , the node in the bank or enterprise layer is a healthy node (susceptible state).
$I_{A(B)}(t)$	At time t , the node in the bank or enterprise layer is a default node (infected state).
$R_{A(B)}(t)$	At time t , the node in the bank or enterprise layer is a default node (infected state).
$\lambda_{A(B)}$	The probability that a susceptible node in the bank (enterprise) layer is infected by adjacent nodes within the layer.
$\lambda_{AB(BA)}$	The probability that a healthy node in the bank (enterprise) layer is infected by adjacent nodes in the enterprise (bank) layer.
$\alpha_{A(B)}$	The probability that an immune node in the two-layer network becomes a susceptible node.
$\beta_{A(B)}$	The probability that a default node in the two-layer network becomes an immune node.
$\mu_{A(B)}$	The probability that a susceptible node in the two-layer network becomes an immune node.
$k_{A(B)}$	The probability that a susceptible node in the two-layer network becomes an immune node.
$P_{A(B)}$	Degree distribution in the bank (enterprise) network.

Assuming that at the initial moment, the loan size in the CRT market remains unchanged, the sum of different types of bank nodes in the bank network is always equal to the total number of bank nodes at any given time, satisfying the following relationship: $S_A(t) + I_A(t) + R_A(t) = M$. In the enterprise credit network, the sum of different types of enterprise nodes is always equal to the total number of enterprise nodes at any given time, satisfying the following relationship:

$$S_B(t) + I_B(t) + R_B(t) = N.$$

At time t , the relative density of bank nodes with degree k_A , denoted as $s_{k_A}(t)$, $i_{k_A}(t)$, $r_{k_A}(t)$, satisfies the following relationship $s_{k_A}(t) + i_{k_A}(t) + r_{k_A}(t) = 1$. Similarly, at time t , the relative density of enterprise nodes with degree k_B , denoted as $s_{k_B}(t)$, $i_{k_B}(t)$, $r_{k_B}(t)$, satisfies the following relationship

$$s_{k_B}(t) + i_{k_B}(t) + r_{k_B}(t) = 1.$$

Based on the above assumptions and the bank-enterprise credit risk contagion mechanism shown in **Figure 1**, the system dynamics equation for bank-enterprise credit risk contagion in the CRT market can be represented as:

$$\left\{ \begin{aligned}
 \frac{ds_{k_A}(t)}{dt} &= -[\lambda_A k_A \theta_1(t) + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2(t)] s_{k_A}(t) - \mu_A s_{k_A}(t) + \alpha_A r_{k_A}(t) \\
 \frac{di_{k_A}(t)}{dt} &= [\lambda_A k_A \theta_1(t) + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2(t)] s_{k_A}(t) - \beta_A i_{k_A}(t) \\
 \frac{dr_{k_A}(t)}{dt} &= \mu_A s_{k_A}(t) + \beta_A i_{k_A}(t) - \alpha_A r_{k_A}(t) \\
 \frac{ds_{k_B}(t)}{dt} &= -[\lambda_B k_B \theta_2(t) + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1(t)] s_{k_B}(t) - \mu_B s_{k_B}(t) + \alpha_B r_{k_B}(t) \\
 \frac{di_{k_B}(t)}{dt} &= [\lambda_B k_B \theta_2(t) + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1(t)] s_{k_B}(t) - \beta_B i_{k_B}(t) \\
 \frac{dr_{k_B}(t)}{dt} &= \mu_B s_{k_B}(t) + \beta_B i_{k_B}(t) - \alpha_B r_{k_B}(t)
 \end{aligned} \right. \tag{1}$$

Among which,
$$\theta_1(t) = \frac{1}{\langle k_A \rangle} \sum_{k_A} k_A P(k_A) i_{k_A}(t) \tag{2}$$

$$\theta_2(t) = \frac{1}{\langle k_B \rangle} \sum_{k_B} k_B P(k_B) i_{k_B}(t) \tag{3}$$

$\theta_1(t)$ represents the probability of randomly selecting an edge from a susceptible state bank node S_A with degree k_A at time t that is connected to a default state bank node I_A , and $\theta_2(t)$ represents the probability of randomly selecting an edge from a susceptible state enterprise S_B node with degree k_B at time t that is connected to a default state enterprise node I_B .

3. Credit Risk Transition Probability Analysis

3.1. Factors Affecting the Probability of Credit Risk Contagion in the Bank Network

In the CRT market, banks in a healthy state primarily transition to default banks due to factors such as insufficient capital adequacy, excessive loan concentration, and overexposure to risky investments; Infectious banks refer to susceptible banks with weak risk defense measures that are infected during the risk transmission process; Immune banks are those with a sound risk management system and effective defense measures against risk. The main factors contributing to the formation and complexity of credit risk contagion in the bank network within the CRT market include:

- 1) Capital Adequacy Ratio δ ($0 < \delta < 1$)

Banks with lower capital adequacy ratios are more likely to trigger crisis finances during economic turmoil, be exposed to external shocks, and increase risk contagion among banks [23]. Banks with higher capital adequacy ratios are able to provide greater risk absorption and mitigate external risk contagion during crises. [24].

- 2) Climate Change γ ($0 < \gamma < 1$)

The study finds that an increase in the annual average temperature significantly elevates the credit risk levels of commercial banks. Heterogeneity analysis reveals

that smaller banks, rural commercial banks, and banks with higher levels of marketization are more sensitive to climate change. The impact of climate change shocks (γ) on bank credit risk is multifaceted, including physical risks, transition risks, financial market volatility, socioeconomic effects, as well as the bank's own risk management and adaptive capacity. These interacting factors may lead to an increase in bank credit risk [25] [26].

3) Risk resistance of banks σ ($0 < \sigma < 1$)

Banks that are well-prepared in terms of capital reserves become more risk-resistant, and banks that are risk-resistant are not only able to stabilize their own operations during a crisis, but also enhance the confidence of their customers and the market in the financial system as a whole [27].

In addition, when firms default on credit, such defaults can be transmitted to banks through the network of credit linkages between banks and firms, thus leading to a further increase in bank credit risk. The probability of contagion from corporate credit risk to bank credit risk.

Therefore, the contagion rate is defined as:

$$\lambda_A = \gamma \lambda_{BA}^{1+\gamma} \frac{1}{2} \left(1 - e^{-\frac{1}{\sigma\delta}} \right) \quad (4)$$

3.2. Factors Affecting the Probability of Corporate Online Credit Risk Contagion

In the enterprise-related network, one of the enterprises in the associated enterprises is infected by the associated credit risk (the probability of default increases), if the enterprises associated with them take timely assistance in the form of financial relief (such as compensation, capital borrowing, commercial credit, etc.), it can reduce the possibility of default of the enterprise, and thus reduce the impact of the associated credit risk on the network of associated enterprises.

In an enterprise's credit-related network, companies of different sizes form interrelated relationships in different ways, such as transaction-related, guarantee-related, asset-liability-related, cross-shareholding and so on. These associations provide a channel for credit risk contagion when credit defaults are caused by corporate mismanagement or by macroeconomic fluctuations. In the enterprise credit correlation network B , when an enterprise in the correlation is infected by the correlation credit risk, if the enterprises associated with it take timely assistance in the form of financial relief (such as substitute payment, capital borrowing, commercial credit, etc.), it can reduce the probability of default of that enterprise, and thus reduce the impact of the correlation credit risk on the correlation network of the correlation enterprises. The probability of enterprise risk contagion is affected by the following factors:

1) Information Disclosure Coefficient τ ($0 < \tau < 1$)

An increase in the information disclosure coefficient τ leads to more extensive information disclosure, meaning that the more comprehensive, timely, and transparent the information disclosed by enterprises to the market, the more ef-

fectively it can suppress the occurrence of credit risk.

2) Climate Transition Risk (CTR) factor ϕ ($0 < \phi < 1$)

Theoretical research indicates that climate transition risks can impair a company's ability to repay its debts, thereby increasing its credit risk. The CTR factor has an asymmetric impact on credit risk, with a positive and significant effect on the credit risk of companies that are highly susceptible to CTR. Specifically, an increase (decrease) in the CTR factor reflects an increase (decrease) in climate transition risk, which in turn reflects an increase (decrease) in credit risk. (Andrea Ugolini, 2024).

3) Market Liquidity of Corporate Assets χ ($0 < \chi < 1$)

High market liquidity of assets allows companies to quickly liquidate their assets without significantly affecting their prices. This facilitates rapid adjustments to their balance sheets in the face of credit risks, thereby reducing the likelihood of credit risk transmission. However, when market liquidity declines, companies may face difficulties in quickly selling assets and may not be able to raise sufficient funds to cope with credit risks. This increases the probability of default and, consequently, the likelihood of credit risk transmission.

Additionally, when banks experience credit risk or financial crises that lead to liquidity shortages or defaults, such defaults can spread to enterprises through the credit linkages between banks and firms. This results in enterprises facing financing difficulties, which further increases their credit risk. The probability of bank credit risk λ_{AB} transmission to enterprise credit risk is represented by the transmission rate. Therefore, the transmission rate λ_{AB} can be defined as:

$$\lambda_B = (\lambda_{AB}\phi)^{e+\chi} \tag{5}$$

3.3. Construction and Analysis of Infection Models

Based on the analysis of the credit risk contagion mechanism of banking firms above and the mean field theory, the behavior of credit risk dynamics in the bank credit correlation network can be portrayed by the following set of differential equations:

$$\begin{cases} \frac{ds_{k_A}(t)}{dt} = -[\lambda_A k_A \theta_1(t) + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2(t)] s_{k_A}(t) - \mu_A s_{k_A}(t) + \alpha_A r_{k_A}(t) \\ \frac{di_{k_A}(t)}{dt} = [\lambda_A k_A \theta_1(t) + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2(t)] s_{k_A}(t) - \beta_A i_{k_A}(t) \\ \frac{dr_{k_A}(t)}{dt} = \mu_A s_{k_A}(t) + \beta_A i_{k_A}(t) - \alpha_A r_{k_A}(t) \end{cases} \tag{6}$$

According to Equation (6), for the steady state condition

$$\begin{cases} \frac{ds_{k_A}(t)}{dt} = 0 \\ \frac{di_{k_A}(t)}{dt} = 0 \\ s_{k_A}(t) + i_{k_A}(t) + r_{k_A}(t) = 1 \end{cases} \tag{7}$$

Then

$$i_{k_A}(t) = \frac{\alpha_A [\lambda_A k_A \theta_1(t) + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2(t)]}{(\alpha_A + \beta_A) [\lambda_A k_A \theta_1(t) + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2(t)] + \beta_A (\alpha_A + \mu_A)} \quad (8)$$

due to
$$\theta_1(t) = \frac{1}{\langle k_A \rangle} \sum_{k_A} k_A P(k_A) i_{k_A}(t) \quad (9)$$

where $\langle k_A \rangle$ denotes the average degree of credit risk contagion in the banking network due to $\langle k_A \rangle = \sum_{k_A} k_A P(k_A)$, $\langle k_A^2 \rangle = \sum_{k_A} k_A^2 P(k_A)$, then

$$\theta_1(t) = \frac{1}{\langle k_A \rangle} \sum_{k_A} k_A P(k_A) \frac{\alpha_A [\lambda_A k_A \theta_1(t) + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2(t)]}{(\alpha_A + \beta_A) [\lambda_A k_A \theta_1(t) + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2(t)] + \beta_A (\alpha_A + \mu_A)} \quad (10)$$

It is known that $\theta_1^* = \theta_1(t)$, Equation (10) has a nontrivial solution, $\theta_1^* = 0$, and if Equation (10) has no nontrivial solution, then $\theta_1^* \neq 0$, then the necessary condition becomes:

$$\frac{d}{d\theta_1^*} \left(\frac{1}{\langle k_A \rangle} \sum_{k_A} k_A P(k_A) \frac{\alpha_A [\lambda_A k_A \theta_1^* + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2^*]}{(\alpha_A + \beta_A) [\lambda_A k_A \theta_1^* + \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2^*] + \beta_A (\alpha_A + \mu_A)} \right) \Big|_{\theta_1^*=0} \geq 1 \quad (11)$$

accordingly,
$$\frac{1}{\langle k_A \rangle} \sum_{k_A} k_A P(k_A) \frac{\alpha_A \lambda_A k_A \beta_A (\alpha_A + \mu_A)}{[(\alpha_A + \beta_A) \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2^* + \beta_A (\alpha_A + \mu_A)]^2} \geq 1 \quad (12)$$

Therefore, the probability of bank credit risk transmission is given by R_{A_0} :

$$R_{A_0} = \frac{\alpha_A \beta_A (\alpha_A + \mu_A) \sum_{k_A} k_A^2 P(k_A) \lambda_A}{[(\alpha_A + \beta_A) \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2^* + \beta_A (\alpha_A + \mu_A)]^2 \sum_{k_A} k_A P(k_A)} \quad (13)$$

Substituting $\lambda_A = \gamma \lambda_{BA}^{1+\gamma} \left(1 - e^{-\frac{1}{\sigma \delta}}\right)$ into the equation, obtain:

$$R_{A_0} = \frac{\alpha_A \beta_A (\alpha_A + \mu_A) \sum_{k_A} k_A^2 P(k_A) \gamma \lambda_{BA}^{1+\gamma} \left(1 - e^{-\frac{1}{\sigma \delta}}\right)}{[(\alpha_A + \beta_A) \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2^* + \beta_A (\alpha_A + \mu_A)]^2 \sum_{k_A} k_A P(k_A)} \quad (14)$$

Further simplifying, obtain:

$$R_{A_0} = \frac{\alpha_A \beta_A (\alpha_A + \mu_A) \gamma \lambda_{BA}^{1+\gamma} \left(1 - e^{-\frac{1}{\sigma \delta}}\right) \langle k_A^2 \rangle}{[(\alpha_A + \beta_A) \lambda_{BA} \lambda_B \langle k_B \rangle \theta_2^* + \beta_A (\alpha_A + \mu_A)]^2 \langle k_A \rangle} \quad (15)$$

R_{A_0} represents the infection probability that a defaulting bank can infect other susceptible banks before transitioning to an immune state. It is a critical indicator that reflects whether risk will spread between banks. $R_{A_0} = 1$ is a threshold value, indicating that risk will continue to propagate stably, neither causing a widespread epidemic nor gradually fading away, with the number of defaulting banks remaining in balance. When $R_{A_0} < 1$, bank credit risk gradually disappears in the bank-enterprise credit network. When $R_{A_0} > 1$, it means the number of defaulting banks increases, and the probability of credit risk transmission between banks becomes

greater, signaling that the risk has global contagion characteristics. The larger the value of R_{A_0} , the more susceptible banks a single defaulting bank can infect during its default period, leading more banks into default and causing the widespread propagation of credit risk.

Similarly, the credit risk dynamics in the enterprise credit network can be described by the following system of differential equations:

$$\begin{cases} \frac{ds_{k_B}(t)}{dt} = -[\lambda_B k_B \theta_2(t) + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1(t)] s_{k_B}(t) - \mu_B s_{k_B}(t) + \alpha_B r_{k_B}(t) \\ \frac{di_{k_B}(t)}{dt} = [\lambda_B k_B \theta_2(t) + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1(t)] s_{k_B}(t) - \beta_B i_{k_B}(t) \\ \frac{dr_{k_B}(t)}{dt} = \mu_B s_{k_B}(t) + \beta_B i_{k_B}(t) - \alpha_B r_{k_B}(t) \end{cases} \quad (16)$$

According to Equation (16), under steady-state conditions:

$$\begin{cases} \frac{ds_{k_B}(t)}{dt} = 0 \\ \frac{di_{k_B}(t)}{dt} = 0 \\ s_{k_B}(t) + i_{k_B}(t) + r_{k_B}(t) = 1 \end{cases} \quad (17)$$

Then,

$$i_{k_B}(t) = \frac{\alpha_B [\lambda_B k_B \theta_2(t) + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1(t)]}{(\alpha_B + \beta_B) [\lambda_B k_B \theta_2(t) + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1(t)] + \beta_B (\alpha_B + \mu_B)} \quad (18)$$

Due to
$$\theta_2(t) = \frac{1}{\langle k_B \rangle} \sum_{k_B} k_B P(k_B) i_{k_B}(t) \quad (19)$$

where $\langle k_B \rangle$ denotes the average degree of credit risk contagion in the enterprise network due to $\langle k_B \rangle = \sum_{k_B} k_B P(k_B)$, $\langle k_B^2 \rangle = \sum_{k_B} k_B^2 P(k_B)$, then

$$\theta_2(t) = \frac{1}{\langle k_B \rangle} \sum_{k_B} k_B P(k_B) \frac{\alpha_B [\lambda_B k_B \theta_2(t) + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1(t)]}{(\alpha_B + \beta_B) [\lambda_B k_B \theta_2(t) + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1(t)] + \beta_B (\alpha_B + \mu_B)} \quad (20)$$

It is known that $\theta_2^* = \theta_2(t)$, Equation (20) has a nontrivial solution, $\theta_2^* = 0$, and if Equation (20) has no nontrivial solution, then $\theta_2^* \neq 0$, then the necessary condition becomes:

$$\frac{d}{d\theta_2^*} \left(\frac{1}{\langle k_B \rangle} \sum_{k_B} k_B P(k_B) \frac{\alpha_B [\lambda_B k_B \theta_2^* + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1^*]}{(\alpha_B + \beta_B) [\lambda_B k_B \theta_2^* + \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1^*] + \beta_B (\alpha_B + \mu_B)} \right) \Big|_{\theta_2^*=0} \geq 1 \quad (21)$$

Accordingly,

$$\frac{1}{\langle k_B \rangle} \sum_{k_B} k_B P(k_B) \frac{\alpha_B \lambda_B k_B \beta_B (\alpha_B + \mu_B)}{[(\alpha_B + \beta_B) \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1^* + \beta_B (\alpha_B + \mu_B)]^2} \geq 1 \quad (22)$$

Therefore, the probability of enterprise credit risk transmission is given by R_{B_0} :

$$R_{B_0} = \frac{\alpha_B \beta_B (\alpha_B + \mu_B) \sum_{k_B} k_B^2 P(k_B) \lambda_B}{[(\alpha_B + \beta_B) \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1^* + \beta_B (\alpha_B + \mu_B)]^2 \sum_{k_B} k_B P(k_B)} \quad (23)$$

Substituting $\lambda_B = (\lambda_{AB}\phi)^{e+\tau\chi}$ into the equation, obtain:

$$R_{B_0} = \frac{\alpha_B \beta_B (\alpha_B + \mu_B) \sum_{k_B} k_B^2 P(k_B) (\lambda_{AB}\phi)^{e+\tau\chi}}{\left[(\alpha_B + \beta_B) \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1^* + \beta_B (\alpha_B + \mu_B) \right]^2 \sum_{k_B} k_B P(k_B)} \quad (24)$$

Further simplifying, obtain:

$$R_{B_0} = \frac{\alpha_B \beta_B (\alpha_B + \mu_B) (\lambda_{AB}\phi)^{e+\tau\chi} \langle k_B^2 \rangle}{\left[(\alpha_B + \beta_B) \lambda_{AB} \lambda_A \langle k_A \rangle \theta_1^* + \beta_B (\alpha_B + \mu_B) \right]^2 \langle k_B \rangle} \quad (25)$$

R_{B_0} represents the infection probability that a defaulted enterprise can infect other susceptible enterprises before transitioning to an immune state. It is a critical indicator reflecting whether risk will propagate across enterprises. $R_{B_0} = 1$ is a threshold, indicating that risk will continue to spread stably, neither spreading on a large scale nor gradually dissipating, with the number of defaulted enterprises remaining balanced. When $R_{B_0} < 1$, enterprise credit risk gradually disappears in the bank-enterprise credit network. When $R_{B_0} > 1$, the number of infected enterprises increases, the probability of enterprise credit risk transmission rises, and the risk exhibits global contagiousness. A larger R_{B_0} means that a single defaulted enterprise will infect more susceptible enterprises during the default period, causing more enterprises to default, thereby leading to widespread credit risk transmission.

4. Experimental Results and Analysis

To ensure the reproducibility of the credit risk contagion simulation, the generation process for the bank-enterprise two-layer network is strictly defined as follows.

Topology Generation: WS Small-World Network: Starting from a ring lattice with N nodes and K nearest neighbors, each edge is rewired with a probability $p = 0.1$ to capture the “small-world” effect of high clustering and short path lengths.

BA Scale-Free Network: Constructed using the preferential attachment mechanism, where new nodes are more likely to connect to existing high-degree “hubs,” resulting in a power-law degree distribution that reflects the systemic importance of large financial institutions.

Numerical simulation analysis is a tool and method based on computer technology. It is often the most effective method for testing when large amounts of empirical time series data are unavailable. In this study, we assume the initial parameters for the CRT market bank-enterprise credit risk contagion SIRS model are as follows:

$$k_A = k_B = 500, \quad \mu_A = \mu_B = 0.2, \quad \alpha_A = \alpha_B = 0.2, \quad \beta_A = \beta_B = 0.2, \quad \sigma = 0.4, \\ \lambda_{BA} = 0.09, \quad \lambda_{AB} = 0.1, \quad \delta = \chi = 0.2, \quad \tau = 0.3, \quad \gamma = \phi = 0.1, \quad \langle k_A \rangle = \langle k_B \rangle = 9, \\ \theta_1^* = \theta_2^* = 0.5, \quad \lambda_A = \lambda_B = 0.4.$$

The calibration of these benchmark parameters is grounded in the stylized facts of financial networks, prior literature on epidemic-based risk contagion, and the specific macroeconomic scenarios of climate risk. First, regarding the network to-

poloogy, the node scales ($k_A = k_B = 500$) and average degrees ($\langle k_A \rangle = \langle k_B \rangle = 9$) are set to reflect the typical sparse yet locally clustered characteristics of regional bank-enterprise credit networks. Second, the cross-layer contagion rates are calibrated to capture the asymmetric feedback loops inherent in the CRT market: the bank “loan withdrawal” effect ($\lambda_{AB} = 0.1$) and the firm-to-bank default spillover ($\lambda_{BA} = 0.09$) reflect the realistic friction and delay in cross-sector risk transmission. Third, the state transition parameters (such as $\alpha_A = \alpha_B = 0.2$, $\beta_A = \beta_B = 0.2$) imply an average financial recovery cycle of approximately 5 periods under standard macroprudential interventions. Finally, parameters representing external environmental shocks and systemic resistance, such as the climate shock intensity ($\sigma = 0.4$) and risk tolerance thresholds ($\theta_1^* = \theta_2^* = 0.5$), are calibrated to simulate a moderate-to-severe climate stress test scenario. This setup ensures that the simulation effectively captures the nonlinear amplification of credit risk under climate physical and transition shocks without deviating from plausible economic realities.

Complex networks can be classified into regular networks, small-world networks, scale-free networks, and random networks. While regular networks and small-world networks resemble uniform networks, many real-world networks are more akin to scale-free networks. Therefore, this paper focuses on discussing the evolutionary characteristics of bank-enterprise credit risk contagion under the two network structures: WS small-world networks and BA scale-free networks.

4.1. Single Influencing Factors of Credit Risk Contagion in Bank Networks

To describe the evolutionary characteristics of credit risk contagion in banks, this study simulates the evolution of credit risk contagion in bank networks under different parameters. The parameters include the capital adequacy ratio δ , climate change shocks γ , the bank’s risk resistance capacity σ , and the contagion probability of credit risk from enterprises to banks λ_{BA} . By adjusting these parameters, the study examines how various factors influence the spread of credit risk across the banking network.

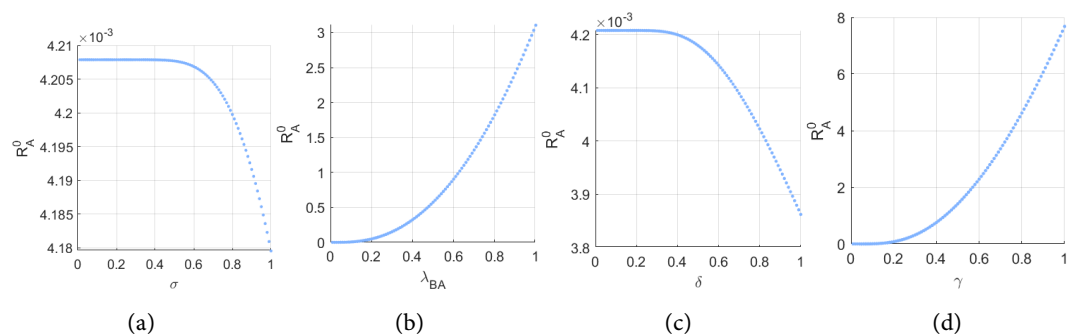


Figure 3. The impact of a single factor on the contagion of credit risk in the banking network under the WS network is shown. (a), (b), (c), and (d) refer to the bank’s risk resistance capacity σ , the contagion probability of credit risk from enterprises to banks λ_{BA} , capital adequacy ratio δ , and climate change shocks γ , respectively.

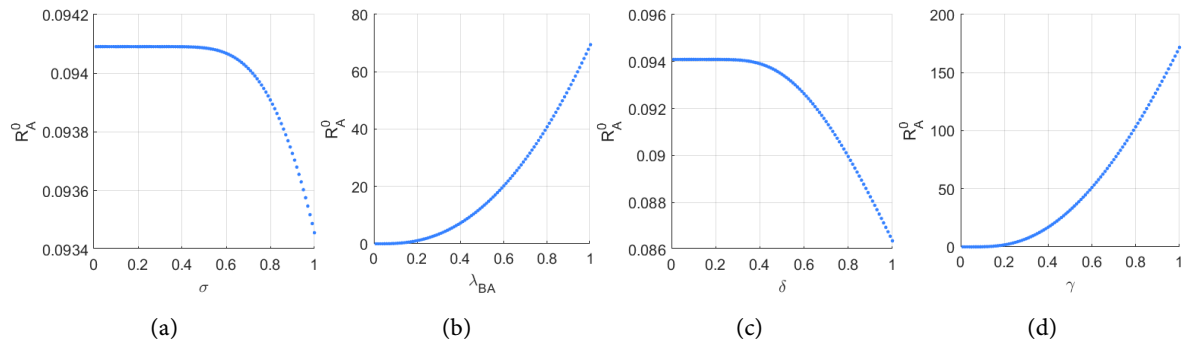


Figure 4. The impact of a single factor on the transmission of credit risk in the banking network under the BA network structure. (a), (b), (c), and (d) represent the bank's risk resistance capacity σ , the probability of transmission of corporate credit risk to banking credit risk λ_{BA} , capital adequacy ratio δ , and climate change shock δ , respectively.

Figure 3(a), **Figure 3(c)** and **Figure 4(a)**, **Figure 4(c)** indicate that in both WS small-world networks and BA scale-free networks, as the bank's risk resistance capacity σ and capital adequacy ratio δ increase, the probability of credit risk transmission in the banking network exhibits a diminishing marginal trend. A comparison reveals that when the bank's risk resistance capacity σ is below 0.6 or the capital adequacy ratio δ is below 0.4, the changes in the probability of credit risk transmission in the banking network are relatively small. Once these thresholds are surpassed, the speed of change in the probability of credit risk transmission in the banking network accelerates, although the overall change in the probability remains insignificant. This suggests that in the credit risk transfer market, when banks have lower risk resistance capacity and capital adequacy ratios, their sensitivity to credit risk increases, possibly necessitating additional credit risk transfer tools, such as credit default swaps (CDS) or asset-backed securities (ABS), to address potential credit risks. As banks improve their capital adequacy and risk resistance capacity, they can effectively suppress the spread of credit risk.

As shown in **Figure 3(b)** and **Figure 4(b)**, the probability of credit risk transmission in the banking network increases marginally as the probability of credit risk transmission from enterprises to banks λ_{BA} rises. When the probability of credit risk transmission from enterprises to banks λ_{BA} is below 0.4, the increase in the probability of credit risk transmission in the banking network is relatively slow. However, when this probability λ_{BA} exceeds 0.4, the increase in the probability of credit risk transmission in the banking network becomes more rapid. This suggests that as enterprise credit risk increases, the credit linkage between enterprises and banks becomes stronger. Poor financial conditions of enterprises (such as bankruptcy or default) can directly impact the quality of assets, capital adequacy, and liquidity of banks, thereby exposing them to higher default risk.

From **Figure 3(b)** and **Figure 4(b)**, it can be observed that in the banking network, an increase in the climate change shock γ leads to an increase in the probability of credit risk transmission. When the climate change shock γ is less than 0.2, the probability of credit risk transmission increases insignificantly. When the climate change shock γ is between 0.2 and 0.6, the increase in the probability of

credit risk transmission is slow. However, when the climate change shock γ exceeds 0.6, the probability increases rapidly. This indicates that under low levels of climate shock, the credit risk transmission in the banking network is relatively moderate, likely mainly triggered by economic or policy fluctuations. Before the critical threshold of the climate change shock γ is reached, the probability of credit risk transmission increases slowly, suggesting that the effects of climate change are beginning to gradually manifest. Once the climate change shock γ exceeds the threshold, the probability of credit risk transmission increases steadily, which may indicate that after extreme weather events or environmental policy changes triggered by climate change reach a certain threshold, the risks within the banking system begin to diffuse rapidly. This shows that the interconnections between banks are intensifying, leading to a faster spread of climate-related risks across the banking sector, potentially causing systemic financial risk. This trend reflects the potential threat that climate change poses to the stability of the financial system. Particularly during large-scale environmental fluctuations, policy adjustments, or market transformations driven by climate change, the transmission of credit risk between banks may gradually escalate. This also highlights the need for financial institutions to place greater emphasis on climate risk management and related capital adequacy requirements.

Due to the differences in network topologies, in the WS small-world network, the node distribution is uniform, and the risk propagation paths are relatively balanced. The impact of parameter changes such as banks' risk resistance σ , the risk contagion probability of corporate credit risk contagion to bank λ_{BA} , capital adequacy δ , and climate change shocks γ on the probability of bank credit risk transmission is weak, indicating that the uniform network structure provides a certain robustness to risk diffusion. In the BA scale-free network, the node distribution is uneven, with high-degree nodes (referred to as "hub nodes") playing a key role in risk diffusion. As shown in the figure, the impact of parameter changes such as banks' risk resistance σ , the risk contagion probability of corporate credit risk contagion to bank λ_{BA} , capital adequacy δ , and climate change shocks γ on the probability of bank credit risk transmission is more significant, especially the risk contagion probability of corporate credit risk contagion to bank λ_{BA} and climate change shocks γ . This suggests that the presence of high-degree nodes significantly amplifies the effect of risk transmission.

Therefore, as shown in **Figure 3** and **Figure 4**, factors such as capital adequacy δ , climate change shocks γ , bank risk resistance σ , and the probability of enterprise credit risk transmission to banks λ_{BA} all influence the probability of bank credit risk transmission. As climate change shocks γ and the probability of enterprise credit risk transmission to banks λ_{BA} increase, it may lead to the spread of risk throughout the entire bank-enterprise network, thus triggering large-scale credit risk transmission. However, capital adequacy δ and risk resistance σ are not the dominant factors in the bank-enterprise network. If strategies for controlling bank credit risk transmission are based solely on individual influencing factors, their effectiveness will be limited.

4.2. Multiple Influences on Banks' Cyber Credit Risk Contagion

Since a single parameter change may not be sufficient to fully reduce the probability of credit risk contagion in banking networks R_{A_0} , a joint optimization of multiple parameters is needed. Therefore, the analysis of multiple influencing factors of credit risk contagion in banking network is carried out under two different network structures, WS small-world network and BA scale-free network.

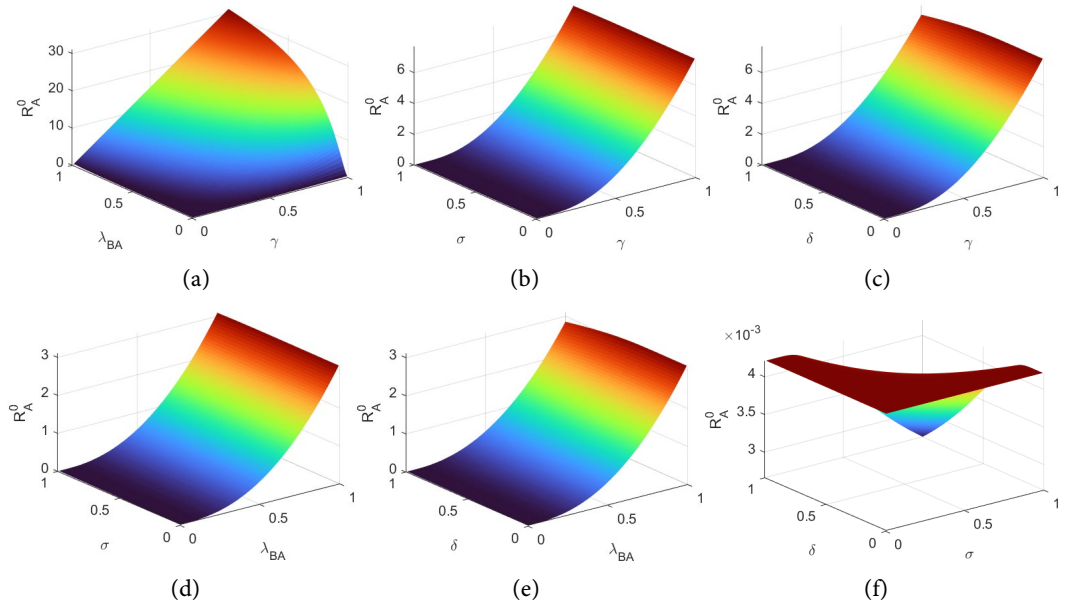


Figure 5. Interaction effect of multiple factors on credit risk contagion in bank network under WS network.

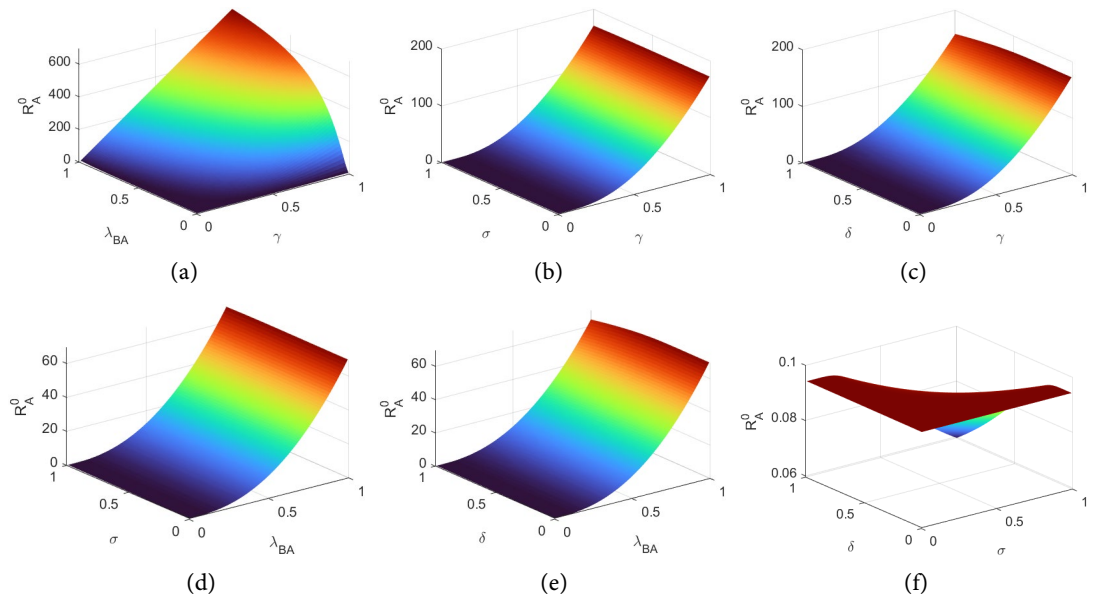


Figure 6. Interaction effect of multiple factors on credit risk contagion in banking network under BA network.

Figure 5 and Figure 6 show the effects of the interaction between capital adequacy ratio δ , climate change impact γ , bank risk resilience σ , and the prob-

ability of credit risk contagion from enterprises to banks λ_{BA} on the probability of credit risk contagion in the banking network R_{A_0} . From **Figure 5(a)** and **Figure 6(a)**, it can be seen that as the probability of credit risk contagion from enterprises to banks λ_{BA} increases, the probability of credit risk contagion in the banking network rises rapidly, especially under high climate change impact γ ($\gamma > 0.5$) conditions, where the increase is particularly significant and exhibits non-linear growth. When the probability of credit risk contagion from enterprises to banks λ_{BA} is less than 0.3, the increase in climate change impact γ gradually amplifies the effect on the probability of credit risk contagion in the banking network. This implies that in the CRT market, when enterprises face default risks, banks, as credit providers, often hold enterprise debt or other related financial assets. As the enterprise credit risk rises, the contagion risk to banks also increases, leading to a higher probability of credit risk contagion in the banking network. Moreover, high climate change impact (such as extreme climate events, climate policy changes, etc.) not only directly affects the financial health of enterprises but also intensifies the risk contagion between enterprises and banks. When enterprises face the pressures of climate change, they may fail to meet their debt obligations on time, thereby triggering credit risk contagion in the banking network.

Figure 5(b), **Figure 5(c)** and **Figure 6(b)**, **Figure 6(c)** show that under the interaction of bank risk resilience σ , capital adequacy ratio δ , and climate change impact γ , the probability of credit risk contagion in the banking network increases as the bank's risk resilience σ , capital adequacy ratio δ , and climate change impact γ increase. When bank risk resilience σ and capital adequacy ratio δ are low, an increase in climate change impact γ leads to a rapid rise in the probability of credit risk contagion in the banking network. However, as bank risk resilience σ and capital adequacy ratio δ increase, the effect of climate change impact γ on the probability of credit risk contagion in the banking network weakens. This suggests that improving bank risk resilience σ and capital adequacy ratio δ can significantly reduce the probability of credit risk contagion in the banking network caused by climate change impacts γ . Therefore, enhancing the risk resilience and capital adequacy ratio of banks can significantly improve the stability of the banking system and effectively control the adverse impact of climate change on network credit risk contagion. This result highlights the importance for regulatory agencies in the banking sector to focus on improving capital adequacy and risk resilience to mitigate the potential risk contagion effects in the financial system.

Figure 5(d), **Figure 5(e)** and **Figure 6(d)**, **Figure 6(e)** illustrate the joint impact of bank risk resilience σ , capital adequacy ratio δ , and the contagion probability from corporate defaults to banks λ_{BA} on the overall banking network's risk level, the probability of credit risk contagion in the banking network decreases as bank risk resilience σ and the capital adequacy ratio δ improve, while it increases with a higher probability of corporate-to-bank risk spillover λ_{BA} . When bank risk resilience σ and capital adequacy ratio δ are low, an increase in the probability of credit risk contagion from corporate credit risk to banks λ_{BA} signifi-

cantly raises the probability of credit risk contagion in the banking network. However, as risk resilience σ and capital adequacy ratio δ increase, the impact of the contagion probability of corporate credit risk to banks λ_{BA} on the probability of credit risk contagion in the banking network is weakened. Even if the probability of corporate credit risk contagion to banks λ_{BA} is high, the probability of credit risk contagion in the banking network can still remain relatively low as long as the bank has strong risk resilience σ and a high capital adequacy ratio δ . This indicates that improving risk resilience σ can effectively reduce the contagion effect from corporate risks to banks, thereby lowering credit risk. Therefore, even when the probability of corporate credit risk contagion to banks is high, as risk resilience and capital adequacy ratio improve, the probability of credit risk contagion in the banking network decreases.

Figure 5(f) and **Figure 6(f)** indicate that under the interaction of a bank's risk resistance capability σ and capital adequacy ratio δ , the probability of credit risk contagion within the banking network decreases as both the bank's risk resistance capability σ and capital adequacy ratio δ increase. This suggests that capital adequacy and risk resistance have a synergistic effect, with the simultaneous enhancement of both parameters having the most significant impact on reducing the probability of credit risk contagion in the banking network. Therefore, in the CRT market, the risk resistance capability and capital adequacy ratio of banks play a crucial role in mitigating credit risk contagion within the banking network. When a bank has a higher capital adequacy ratio, its capital base is better equipped to absorb potential losses, thereby reducing the spread of risk. A bank's risk resistance capability determines its ability to cope with external credit shocks. An increase in risk resistance enhances the bank's stability and helps to minimize the impact of risk transmission. Furthermore, improving both risk resistance and capital adequacy can effectively reduce the contagion effect of credit risk, particularly during periods of heightened uncertainty in the financial markets. This strengthens the buffer for the banking network, helping to prevent localized risks from escalating into systemic risks.

In addition, the probability of credit risk contagion in the banking network R_{A_0} under the BA network is higher than that under the WS small-world network. This is because the BA network, due to its inherent heterogeneity and the presence of hub nodes, is more sensitive to parameter changes and exhibits lower system stability under high-risk conditions. In contrast, the WS small-world network demonstrates more uniform dynamic responses, making it more suitable for modeling relatively stable systems. The heterogeneity of the BA network is higher than that of the WS small-world network. The higher the network heterogeneity, the more likely the speed, scope, and impact of credit risk diffusion in the banking network will significantly increase, thereby leading to a higher probability of credit risk contagion in the banking network.

Further analysis based on these results reveals that high climate change shocks and high contagion rates between banks and enterprises are the main factors contributing to the increase in the probability of credit risk contagion in the banking

network. The interaction between capital adequacy and banks' risk resistance capabilities plays a significant role in mitigating credit risk contagion in the banking network. Therefore, when formulating strategies to control credit risk contagion in the banking network, it is essential not only to limit the impact of high climate change shocks and high contagion rates between banks and enterprises but also to increase capital adequacy and enhance the banks' risk resistance capabilities. Additionally, efforts should be made to prevent defaults by core banking nodes in the network.

4.3. Single Influencing Factors of Credit Risk Contagion in Corporate Networks

To describe the evolutionary characteristics of bank credit risk contagion, this study simulates the evolution of credit risk contagion in enterprise networks under different parameters by assigning values to various factors, including the information disclosure coefficient τ , climate transition risk (CTR) factor ϕ , market liquidity of enterprise assets χ , and the contagion probability of bank credit risk to enterprise λ_{AB} .

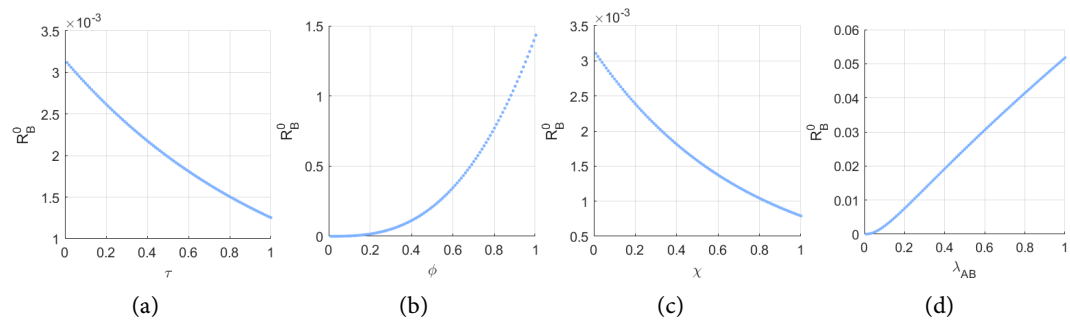


Figure 7. The impact of a single factor on the contagion of credit risk in the enterprise network under the WS network is shown. (a), (b), (c), and (d) refer to the information disclosure coefficient τ , climate transition risk (CTR) factor ϕ , market liquidity of enterprise assets χ , and the contagion probability of bank credit risk to enterprise λ_{AB} , respectively.

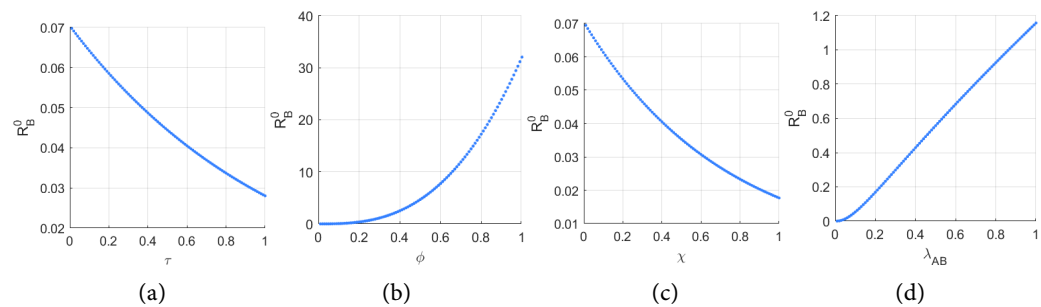


Figure 8. Shows the impact of a single factor on credit risk contagion in enterprise networks under the BA network. (a), (b), (c), and (d) represent the information disclosure coefficient τ , climate transition risk (CTR) factor ϕ , market liquidity of enterprise assets χ , and the contagion probability of bank credit risk to enterprise λ_{AB} , respectively.

Figure 7(a), Figure 7(c) and Figure 8(a), Figure 8(c) indicate that, in both the WS small-world network and the BA scale-free network, as the information dis-

closure coefficient τ and market liquidity χ increase, the probability of credit risk contagion in enterprise networks exhibits a marginally decreasing trend. This trend can be explained primarily by the increase in the information disclosure coefficient τ , which allows market participants to gain a more timely and comprehensive understanding of an enterprise's risk profile. As a result, when an enterprise faces credit risk, the market can identify potential risks earlier and react accordingly. As the information disclosure coefficient increases further, the market's response to the information becomes more pervasive, reducing the marginal effect of information disclosure, leading to a marginal decrease in the probability of credit risk contagion in enterprise networks. Similarly, when market liquidity χ increases, enterprises facing credit risk can more quickly transfer or diversify risk through market operations (e.g., asset sales, financing, etc.). However, once the market reaches a high liquidity level, any further increase in liquidity reduces its ability to suppress the probability of credit risk contagion in enterprise networks.

Figure 7(b) and **Figure 8(b)** show that the probability of credit risk contagion in enterprise networks increases marginally as the climate transition risk (CTR) factor ϕ rises. When the CTR factor ϕ is below 0.5, the probability of credit risk contagion increases slowly, but when the CTR factor ϕ exceeds 0.5, the probability increases rapidly. This suggests that, under low levels of climate transition risk, enterprises bear relatively smaller risks, and the speed of systemic credit risk diffusion is slower. This could be due to the fact that, at lower levels of climate transition risk, enterprises can gradually adapt to changes in climate policies and reduce external shocks through adjustments to their response measures. Once the climate transition risk exceeds a certain threshold, it begins to rapidly amplify the risk propagation effect between enterprises. This implies that as climate transition-related policies become stronger, the pressure on enterprises to transition increases. Enterprises that fail to adapt to the transition may face higher default risks, which in turn intensifies the credit risk contagion across the entire enterprise network. This trend indicates that an increase in climate transition risk may, to some extent, exacerbate the spread of credit risk between enterprises, especially when companies fail to timely adapt to climate policies or changes in market demands. Once the climate transition risk reaches a critical point, credit risk contagion may spread rapidly, further impacting the stability of the entire economy.

From **Figure 7(d)** and **Figure 8(d)**, it can be seen that an increase in the probability of contagion from bank credit risk to corporate λ_{AB} causes an increase in the probability of contagion from corporate credit risk in the corporate network, indicating that in the interrelationship between banks and corporations, an increase in the probability of contagion from bank credit risk to corporate λ_{AB} makes it easier for banking crises to spread to the corporate network. When a bank crisis occurs, it is usually accompanied by liquidity constraints, shortage of funds, etc. Banks may reduce their credit support to enterprises, resulting in difficulties in enterprise financing, and the probability of bank credit risk contagion to enterprises increases due to the credit relationship between banks and enterprises.

Due to the difference in network topology, the high degree of clustering in WS small-world networks makes it easier for risks to be transmitted between local nodes, and the path of risk propagation is relatively even. In WS small-world networks, contagion is usually dominated by local outbreaks, followed by rapid diffusion to the entire network through global efficient connectivity, in which changes in information disclosure coefficients τ are particularly important to the probability of corporate credit risk contagion, because more transparent information can effectively inhibit the accumulation of local risks, thus slowing down the speed of global diffusion. The heterogeneity of BA scale-free networks is larger than that of WS small-world networks, and the local clustering degree of BA scale-free networks is lower, so the initial speed of contagion is relatively even. network has a lower degree of local clustering, and thus the initial rate of contagion is slower. In the BA scale-free network, the climate transition risk (CTR) factor ϕ has a significant impact on the probability of corporate credit risk contagion, which indicates that super nodes with high risk appetite may become the trigger point of systemic crisis, and the probability of contagion from bank credit risk to corporate λ_{AB} is particularly critical to the global spread of corporate credit risk.

4.4. Multiple Influences on Corporate Online Credit Risk Contagion

Similarly, since a single parameter change may not be sufficient to fully reduce the probability of corporate networks credit risk contagion $R_{B_0}^0$, a joint optimization of multiple parameters is required. Therefore, the analysis of multiple influences on bank network credit risk contagion is conducted under two different network structures, WS small-world network and BA scale-free network.

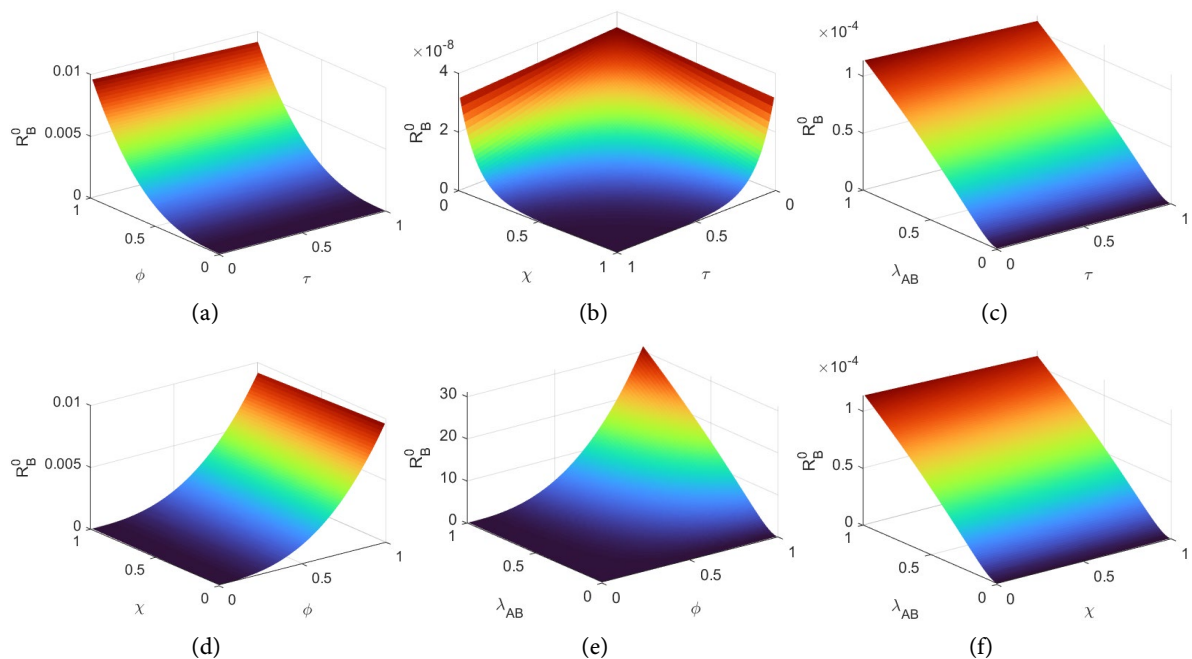


Figure 9. Interaction effects of multiple factors on credit risk contagion in corporate networks under WS networks.

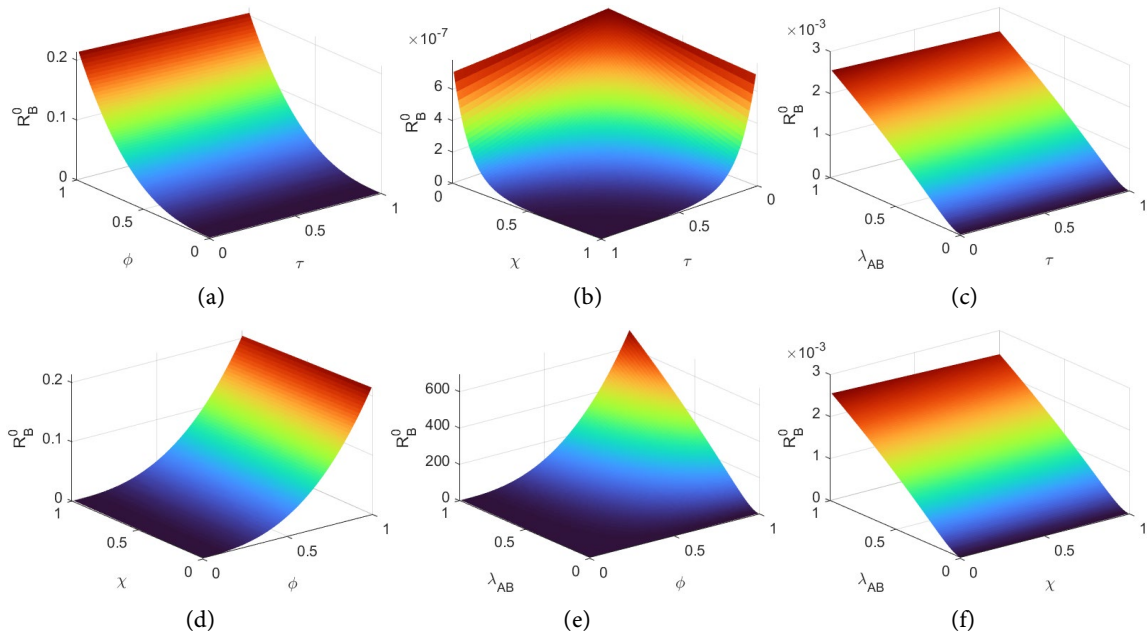


Figure 10. Interaction effects of multiple factors on credit risk contagion in corporate networks under BA networks.

Figure 9(a), Figure 10(a) shows that when the information disclosure coefficient τ interacts with the climate transition risk (CTR) factor ϕ , the probability of corporate credit risk contagion increases with the increase of the climate transition risk (CTR) factor ϕ , and the probability of corporate credit risk contagion decreases with the increase of the climate transition risk (CTR) factor. As the information disclosure coefficient τ increases, the probability of corporate credit risk contagion decreases, which indicates that there is a significant synergistic effect between information disclosure and climate transition risk, and the marginal effect of the information disclosure factor is most significant in the condition of high climate transition risk, the effect of information disclosure is closely related to the level of climate transition risk, and the effect of improving information disclosure is more significant in the environment of high climate transition risk. The effect of information disclosure is closely related to the level of climate transition risk, and the effect of increasing information disclosure is more significant in a high climate transition risk environment. Moreover, a higher disclosure coefficient τ mitigates the effect of the increase in the probability of credit risk contagion by the climate transition risk (CTR) factor ϕ .

Figure 9(b), Figure 10(b) shows that an increase in the disclosure coefficient τ and market liquidity χ leads to a decrease in the probability of corporate credit risk contagion, *i.e.*, more liquid assets and more disclosed firms inhibit the spread of risk, and at the same time, the effect of the disclosure coefficient τ on the probability of corporate credit risk contagion is more pronounced when the market liquidity χ is low, which suggests that disclosure is particularly important in a low liquidity environment.

The interactions between (c) and (f) of the disclosure coefficient τ , market li-

quidity χ and the probability of contagion from bank credit risk to corporate λ_{AB} in **Figure 9** and **Figure 10** indicate that an increase in the probability of contagion from bank credit risk to corporate credit risk leads to an increase in the probability of contagion from corporate credit risk, but when the disclosure coefficient τ and market liquidity χ are increased, the intensity of contagion from corporate credit risk decreases significantly even though the probability of contagion from bank credit risk to corporate λ_{AB} is lower than that from bank credit risk to corporate credit risk, which is the most important in a low-liquidity environment. However, when the coefficient of information disclosure and market liquidity increase, the intensity of corporate credit risk contagion decreases significantly, and even though the probability of credit risk transmission from banks to corporations λ_{AB} is high, increasing information disclosure and market liquidity can still control the risk.

In **Figure 9(d)** and **Figure 10(d)**, it is observed that when market liquidity χ is high, the probability of corporate credit risk contagion remains low even in the presence of high CTR, while high CTR leads to a significant increase in the probability of corporate credit risk contagion when market liquidity χ is low. This suggests that when the (CTR) factor ϕ interacts with market liquidity, higher market liquidity χ significantly mitigates the impact of high climate transition risk on the probability of corporate credit risk contagion.

Figure 9(e), **Figure 10(e)** shows that the probability of corporate credit risk contagion increases as the probability of bank credit risk contagion to corporate λ_{AB} increases, and this increasing trend is more obvious in the region with high climate transition risk (CTR). Moreover, higher values of climate transition risk (CTR) factor ϕ amplify the impact of the probability of transmission of bank credit risk to corporate λ_{AB} , indicating that when the probability of transmission of bank credit risk to corporate λ_{AB} and the CTR factor ϕ are both high, the probability of transmission of corporate credit risk shows an explosive growth, and the probability of transmission of bank credit risk to corporate credit risk shows an explosive growth. It shows that when the probability of credit risk transmission from banks to enterprises and the climate transition risk (CTR) factor are both at high values, the probability of credit risk transmission from enterprises is “explosive”, and the interaction between the probability of credit risk transmission from banks to enterprises λ_{AB} and the climate transition risk (CTR) factor ϕ has a cumulative effect on the probability of credit risk transmission from enterprises.

A comparison of **Figure 9** and **Figure 10** reveals that the impact of parameter interactions on risk is more moderate in the WS small-world network, where the disclosure coefficient τ plays a more prominent role and has a significant mitigating effect on all parameter interactions. In the BA scale-free network, the non-linear effect of parameter interactions on risk is more pronounced, especially in the case of the climate transition risk (CTR) factor ϕ and the increased probability of contagion from bank credit risk to corporate λ_{AB} , and the concentration

of risk contagion.

5. Conclusions

In the context of the Credit Risk Transfer (CRT) market, this paper constructs a bank-enterprise two-layer network model based on SIRS epidemic dynamics. Through theoretical derivation and numerical simulations, we reveal the evolutionary laws of credit risk contagion. The primary findings are as follows:

1) Nonlinear Evolution and Defense Mechanisms of Risk Contagion in Banking Networks

In the interbank credit correlation network, the probability of bank credit risk contagion exhibits significant asymmetric characteristics. On one hand, it shows a diminishing marginal trend as risk resistance capacity and capital adequacy improve; on the other hand, it demonstrates positive sensitivity to cross-layer risk spillovers (from enterprises to banks) and physical climate risks, increasing significantly as both intensify. The interplay between capital adequacy, risk resistance, and physical climate risk reveals a risk attenuation mechanism where increases in assets and resistance significantly suppress contagion triggered by high physical climate shocks and a stability boundary. When assets and risk resistance reach specific thresholds, the contagion probability remains stable regardless of fluctuations in physical climate risk, indicating robust system stability. Capital adequacy and risk resilience constitute the system's endogenous defense line. Their synergy suggests that synchronized improvements in these two indicators represent the optimal solution for reducing systemic risk. This implies that prioritizing these fundamental indicators in risk management can significantly enhance the resilience of the banking network and effectively block the cascading diffusion of risk.

2) Regulatory and Amplification Mechanisms of Enterprise Network Risk

The probability of credit risk contagion in the enterprise network decreases marginally with the improvement of information disclosure quality and market liquidity. Conversely, it increases marginally with the escalation of Climate Transition Risk (CTR) and risk spillovers from banks to enterprises. Furthermore, when information disclosure interacts with the CTR factor, high-quality disclosure mitigates the incremental effect of transition risk on contagion probability. The interaction between information disclosure and market liquidity exhibits a significant synergistic inhibitory effect; that is, simultaneously improving disclosure levels and liquidity can effectively control systemic risk on the enterprise side even under adverse conditions of increasing bank risk spillovers. While higher bank-to-enterprise spillovers drive up contagion probabilities, enhanced disclosure and liquidity remain effective control measures. High market liquidity significantly alleviates the impact of extreme CTR on contagion. However, the interaction between bank-to-enterprise spillover and CTR amplifies the growth of contagion probabilities. In summary, improving information disclosure and market liquidity can mitigate the adverse impacts of climate transition risks and bank risk

spillovers, with more pronounced effects in high-risk scenarios.

3) Structural Impact of Network Topological Heterogeneity

Higher heterogeneity in the bank-enterprise credit correlation network leads to a greater probability of credit risk contagion, indicating that the topological structure significantly dictates contagion intensity. Compared to the WS Small-World network, the BA Scale-Free network exhibits highly uneven connection distributions. This topological heterogeneity facilitates the concentrated dissemination of credit risk, creating high-speed conduits for contagion. This amplifies the potential impact of risk and poses a greater challenge to the overall stability of the network.

In the CRT market, the endogenous defense mechanisms of banks (capital adequacy and risk resilience) are the cornerstones of market stability. Given the high penetration of financial derivatives, strengthening these indicators is essential to curb the spatiotemporal spread of crises. However, physical climate risk possesses a distinct threshold effect; once the threshold is breached, risk will experience explosive growth.

Regulatory recommendations: Authorities should construct a “Twin-Pillar” framework encompassing “Macroprudential Regulation + Climate Adaptation.” For the banking sector, focus should be placed on monitoring the security of core hub nodes to prevent climate risks from triggering systemic collapse. For the corporate sector, policies must balance information disclosure with transition risks while maintaining sufficient market liquidity to absorb transition shocks. Furthermore, severing the vicious risk loop between banks and enterprises is critical to preventing the rapid accumulation of systemic risk.

This paper reveals the dynamic mechanisms and key characteristics of risk evolution in the CRT market, providing theoretical support for regulation. Future research will further focus on the quantitative design and dynamic optimization of specific regulatory policies to propose more operational policy recommendations.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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