

Research on Risk Contagion Mechanism of Financial Markets Based on Complex Network Theory

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Abstract. Against deepening global financial integration, traditional linear risk tools cannot capture time-lagged cascading risk spillovers, while existing epidemic-network studies separately analyze multilayer topology, temporal transmission and node centrality without unified frameworks. This paper develops a temporal multilayer Susceptible-Exposed-Infected-Recovered (SEIR) coupled contagion model integrating time-resolved paths and statistically validated Katz-Bonacich centrality. It sorts three branches of contagion literature and identifies three key defects in prior static, fragmented models. Two progressive dynamic models are constructed, incorporating latent risk states and liquidity-endogenous recovery coefficients. Three core diffusion drivers—network phase-transition traits, time-lagged linkages and asset community heterogeneity—are clarified. These mechanisms jointly explain how local financial shocks can evolve into broader cross-market and cross-sector contagion through interconnected network structures. A multi-tiered governance framework covering micro capital regulation, spectral macro supervision and targeted systemically important financial institution (SIFI) oversight is put forward. The study acknowledges linear vector autoregression (VAR) and exogenous liquidity limitations, and proposes cross-border, fintech-inclusive extensions for follow-up research.

Keywords: systemic financial risk, multilayer contagion network, SEIR epidemic model, macroprudential supervision

1. Introduction

1.1. Research background

Events including the 2008 global financial crisis, the 2020 market turbulence triggered by the COVID-19 pandemic, and the 2022 financial volatility induced by geopolitical conflicts have repeatedly demonstrated that, in a highly interconnected modern financial system, risks do not emerge and dissipate in isolation. The default of a single institution or a downturn in a single market can spread rapidly through channels such as credit interconnections, overlapping asset holdings, liquidity contraction and confidence contagion, triggering chain reactions that eventually escalate into cross-market and cross-sector systemic crises. Traditional risk regulatory frameworks centered on individual institutions—such as standalone capital adequacy requirements and individual value-

at-risk (VaR) measurement—fail to capture such indirect spillover effects of "network cascading amplification", nor can they predict the time lag and path of risk transmission.

Complex network theory provides a systematic analytical tool for characterizing such interconnected risks [1]. By representing financial institutions, markets, and assets as nodes, and business relationships, price co-movements, and spillovers as edges, researchers can quantitatively analyze the impact of network structure on risk propagation, identify systemically important nodes, and simulate the entire process of crisis diffusion. However, existing studies still have notable limitations: most models are based on the static network assumption and ignore the temporal characteristics of risk propagation; centrality indicators are mostly directly adapted from general methods in network science, without statistical calibration for the noise characteristics of financial data; and most contagion models adopt a single-layer network structure, which can hardly fully capture the cross-layer spillovers among banks, real sector enterprises and asset markets.

1.2. Research significance

This study connects two largely separate strands of systemic-risk research, namely multi-layer network contagion simulation and time-varying node importance evaluation. Existing multi-layer SIR models mostly construct networks based on stock tail correlation, which can reflect contagion differences across different association layers, but insufficient discussion has been conducted on the chronological propagation process of cross-financial sector risks [2]. Although existing studies on time-varying networks have proposed temporal higher-order paths to distinguish shock sources from shock transmission carriers, no statistical test has been conducted on centrality indicators [3]. Therefore, this paper incorporates the multi-layer contagion model, time-ordered propagation paths and statistically tested Katz-Bonacich centrality into a unified framework, enabling the formation of a cohesive analytical process integrating network construction, risk simulation and key node identification.

At the regulatory application level, the proposed framework helps address three core questions: where risks originate, through which entities they propagate, and which nodes require priority intervention. The time-varying network approach enables differentiation of the contagion roles played by banks, shadow banks, and insurance companies at different stages of a crisis cycle [3]. The KB centrality measure subjected to statistical significance testing can reduce the risk of unreliable node rankings produced by unvalidated indicators [4]. Meanwhile, the four-layer multiplex structure constructed in this paper can quantify the independent risk spillover effects of industry, geography and tail-related connected channels, assisting regulatory authorities in identifying core contagion hubs in the 2008 and 2020 financial crises [2]. Therefore, this framework can provide a set of quantifiable indicators for cross-sectoral and cross-border risk monitoring, but its early warning performance still requires further validation through out-of-sample testing.

1.3. Research content and framework

Based on the systematization of practical risks in Section 1.1 and the elaboration of research values in Section 1.2, this paper carries out the following three aspects of work on the basis of existing studies by Bozhidarova et al., Franch et al., and Sadeghi and Feinstein [2-4]. First, drawing on the multi-layer SIR framework proposed by Bozhidarova et al., this paper incorporates tail dependence as well as geographical and industrial stratification dimensions to construct a dynamic multiplex network, and meanwhile introduces the time-effective path proposed by Franch et al. to characterize the sequential contagion process [2, 3]. Second, this paper embeds the statistically tested Katz-

Bonacich centrality into the contagion model, and quantifies the risk source attribute, risk propagation attribute and risk reception attribute of nodes during a crisis [4]. Third, this paper compares the prediction accuracy of static multiplex structures and time-varying multiplex structures, and puts forward targeted macroprudential policy measures accordingly. Following the research logic of theoretical framework construction, model simulation, and policy enlightenment, this paper systematically addresses the gap in existing literature where static contagion modeling is disconnected from unverified static topological measures.

2. Literature review

2.1. Literature on financial contagion and multilayer network risk

Current research on financial systemic risk contagion can be broadly divided into two methodological branches: multi-layer financial network simulation and tail dependence econometric modeling. The former focuses on explaining through which inter-agent relationships risks diffuse, while the latter mainly measures the strength of risk comovement under extreme market conditions. The two types of methodologies address the questions of "contagion path" and "contagion magnitude" respectively.

Within multilayer network research, Gao built a static three-agent network covering banks, firms and assets and identified banks' dual roles in containing and spreading risks, yet the model cannot capture time-varying linkage intensities [5]. Dong and Dong developed a dynamic VaR-ES Granger causality network to reflect temporal features but omitted cross-layer links between real firms and financial institutions [6].

Tail dependence models capture abnormal cross-market co-movement amid extreme slumps. Saekow et al. used mixed copulas and Bayesian averaging to measure asymmetric lower-tail linkages across global equities and proved shock types create disparate crisis contagion, yet copulas cannot trace entity-level transmission paths [7]. Current research is fragmented: epidemic models lack statistically verified topological metrics, and copula tail analysis ignores multilayer heterogeneous connections. Prior work only adopts static single-layer networks without jointly modeling multi-agent structures and nonlinear tail spillovers [2, 4]. This paper integrates time-varying multilayer topology and tail risk measurement to fill these gaps.

2.2. Research progress on coupled epidemic-network contagion models

Integrating epidemiological dynamics with financial network topology has become a dominant approach for analyzing nonlinear systemic risk spillovers. Existing relevant research can be broadly categorized into three strands: multi-layer contagion modeling, temporal network analysis, and node significance testing.

Studies in the first strand characterize risk state transitions by extending the Susceptible-Infected-Recovered (SIR) model. Bozhidarova et al. constructed a four-layer multi-layer SIR model based on stock tail dependence, geographic boundaries and industrial classification, which significantly improved the accuracy of crisis prediction, but overlooked the risk propagation with sequential time lags [2]. Liu introduced latent exposed nodes into the basic SIR framework and extended it to the Susceptible-Exposed-Infected-Recovered (SEIR) model, which captured heterogeneous risk vulnerability across banks, insurance companies and shadow banking institutions, but lacked tools to track cross-border dynamic contagion chains [8].

The second strand of research emphasizes the temporal order of edge occurrence. Franch et al. developed a higher-order centrality metric that preserves temporal ordering to classify nodes in cross-border financial sectors as risk sources, spreaders or recipients [3]. However, this temporal metric has not been embedded into the epidemiological differential equation system. Chen et al. combined the Susceptible-Infected-Susceptible (SIS) dynamic model with the stock network filtered by the Planar Maximally Filtered Graph (PMFG), and verified the dominant role of hub nodes during extreme market turmoil, but did not incorporate cross-market multi-layer associations [9].

The third strand of research focuses on the statistical credibility of node ranking results. Sadeghi and Feinstein proposed a statistically rigorous contagion centrality metric to eliminate measurement bias in traditional node ranking measures [4]. Bozhidarova et al. conducted a comprehensive meta-analysis of existing epidemiological network models and pointed out that previous studies rarely consider multi-layer topology, time-varying propagation mechanisms and statistically validated centrality simultaneously within a unified analytical framework [2]. On the whole, existing studies have addressed the problems of risk state transition, temporal path identification and statistical node ranking separately, but have not clarified how these three components interact within the same model. This paper conducts its research exactly at this intersection.

2.3. Literature synthesis

Current research on financial contagion presents three interrelated core gaps. First, existing multi-layer contagion models rely on static firm-level network construction methods and neglect the clustering characteristics of heterogeneous asset communities [2, 10]. Although the four-layer SIR framework designed by Bozhidarova et al. distinguishes the tail layer, geographical layer and industrial layer, it treats all firm nodes equally, and fails to adopt the Louvain community detection method proposed by Nguyen et al. to capture intra-group risk spillover effects [2, 10]. Second, multi-agent three-layer networks separate bank credit connections from cross-asset contagion dynamics [5]. Gao constructed a bank-firm-asset multi-layer system under the isolated shock assumption, but ignored the cross-category spillover effects among stocks, cryptocurrencies and exchange-traded funds (ETFs) documented by Nguyen et al. [5, 10]. Third, most other existing studies generally suffer from three methodological deficiencies simultaneously: time-resolved temporal network tools can capture continuous risk paths, but they fail to denoise high-frequency correlation matrices; random matrix theory based on the Tracy-Widom distribution can filter market noise, but it has not yet been embedded into the contagion simulation process; in addition, traditional topological centrality indicators are not statistically calibrated and contain untested biases [3, 4, 10]. Prior literature fails to integrate temporal network dynamics, community denoising and calibrated centrality within one multilayer SIR framework, only developing isolated single modules and yielding fragmented analysis. Instead of introducing extra network metrics, this paper builds an integrated contagion model incorporating multi-agent layers, asset community identification and statistically validated topological indicators.

3. Theoretical foundation and model construction

3.1. Fundamental theoretical framework for dynamic contagion in financial networks

This framework answers four core questions about financial linkages, time-varying risk transmission, state-dependent node importance and statistical validity, drawing on temporal networks, contagion dynamics, risk-sensitive centrality and multilayer network theory.

Temporal network theory provides a framework for representing the sequence of risk transmission. Franch et al. argue that static aggregated networks misalign cross-period links and overstate node reachability, and formalize tail Granger causality networks spanning banks, insurers and shadow banks [3]. Contagion dynamics depicts node risk state shifts. Bartesaghi et al. combine Susceptible-Infected (SI) epidemic rules with network transmissibility to create stress-adjustable risk-dependent centrality, supporting dynamic contagion weighting [11]. Statistical inference eliminates centrality measurement bias; Sadeghi and Feinstein derive Katz-Bonacich centrality's asymptotic distribution and design significance tests to screen false noise-driven risk signals [4]. Multi-layer network theory is applied to distinguish heterogeneous interconnections among banks, firms and assets, which prevents credit risk, market risk and liquidity risk from being compressed into a single network and complements the aforementioned three single-dimensional theoretical frameworks [10]. The four theories perform the distinct functions of temporal constraint, state transition, node identification and structural stratification respectively, and collectively form the theoretical foundation for the subsequent model in this study.

3.2. Multi-layer SIS epidemic model integrating temporal features

This section elaborates on the construction logic of an integrated model that unifies multi-agent cross-layer connections, time-resolved propagation paths, and the SIS risk diffusion equation, based on the theoretical foundations of multilayer financial networks, temporal topological analysis, and epidemic dynamics proposed by Chen et al., Gao, and Shi et al. [1, 5, 9]. First, Gao introduced a tripartite multilayer financial network framework consisting of three layers: bank-enterprise credit lending, interbank lending, and bank asset portfolio [5]. This framework defines heterogeneous edges among agents, and identifies three independent risk shock sources: corporate credit default, asset depreciation, and bank bankruptcy. Different from the single-layer network setting, this tripartite multilayer structure distinguishes direct contagion between banks from indirect cross-market spillover mediated by enterprises or assets, laying the topological foundation for subsequent epidemic simulation [5].

Second, Chen et al. combined the SIS differential dynamic equation with a stock correlation network filtered by the Planar Maximally Filtered Graph (PMFG), and established the core mathematical specification for the risk infection and recovery process [9]. This model introduces weighted node degree to characterize the hub-driven diffusion effect, and quantifies the risk propagation flow F_i to measure the systemic influence of an individual node; furthermore, it defines the node response time τ_i to capture the time-lag effect of contagion velocity, providing a measurable dynamic indicator for temporal network analysis [9]. However, this study only adopted a static single-market network, and did not incorporate the multi-agent cross-layer correlation constructed by Gao [5].

To address this separation drawback, Shi et al. extended the static epidemic model to a core-periphery multilayer Susceptible-Infected-Recovered-Susceptible (SIRS) framework, calibrated the cross-layer spillover intensity using Conditional Value at Risk (CoVaR), and divided nodes into high-risk core groups and low-risk peripheral groups [1]. The above three bodies of literature jointly support the integrated model design of this paper: the paper embeds the three-layer multi-agent topology proposed by Gao into the SIS dynamic system established by Chen, and adopts the CoVaR-based cross-layer weight calibration method proposed by Shi to construct a multi-contagion equation that conforms to temporal characteristics [1, 5, 9]. The improved model retains the infection/recovery parameter specification from Chen, incorporates the multi-source shock simulation mechanism from Gao, and uses Shi's core-periphery node classification to distinguish

cross-layer heterogeneous infection rates, realizing the organic integration of multilayer topology, temporal dynamic propagation, and epidemic diffusion rules.

3.3. Multilayer SEIR-SIR coupled epidemic dynamics model

Drawing on Bozhidarova et al., Liu, Chen et al., and Cao and Feinstein, this study assumes that institutional distress may involve a latent exposure phase, whereas asset-price shocks may materialize rapidly [2, 8, 9, 12]. The proposed model applies SEIR transitions to financial institutions, retains SIR dynamics for asset markets, and couples the two processes through holdings and liquidity channels. A unified dynamic contagion system incorporates multilayer topology, latent risks and liquidity-price feedback. Bozhidarova et al. built a baseline discrete four-layer SIR contagion equation with this core formula [2]:

$$\frac{dI(t)}{dt} = \beta S(t)I(t) - \gamma I(t) \quad (1)$$

where $S(t)$ denotes the number of susceptible financial nodes that remain in stable operation at time t ; $I(t)$ represents the number of infected nodes that have experienced risk shocks at time t ; β is the baseline risk contagion rate among interconnected enterprises; and γ is the constant recovery rate of distressed entities.

To distinguish the intensity of heterogeneous cross-layer spillovers, this study defines a layer-specific contagion weight for node pair (i, j) as:

$$w_{i,j}^{[\alpha]} = \begin{cases} \hat{\chi}_{i,j}^U \times \beta_1, & \alpha = 1 \\ \beta_\alpha, & \alpha \in \{2, 3, 4\} \end{cases} \quad (2)$$

where $w_{i,j}^{[\alpha]}$ is the risk contagion intensity from firm i to firm j within layer α . $\hat{\chi}_{i,j}^U$ is the upper tail dependence coefficient, which captures the extreme co-movement between the stock returns of the two firms. β_α is the baseline contagion probability that is specific to each layer — namely tail, continental, industry, and global layers.

The classical SIR model disregards the latent risk accumulation process before enterprises fall into distress. Therefore, this paper introduces the extended SEIR framework proposed by Liu, which incorporates the exposed state $E(t)$, and revises the complete four-state differential system as follows [8]:

$$\begin{cases} \frac{dS(t)}{dt} = -\beta S(t)I(t) \\ \frac{dE(t)}{dt} = \beta S(t)I(t) - \sigma E(t) \\ \frac{dI(t)}{dt} = \sigma E(t) - \gamma I(t) \\ \frac{dR(t)}{dt} = \gamma I(t) \end{cases} \quad (3)$$

where $E(t)$ denotes the number of nodes exposed to hidden risks but not yet experiencing a crisis; σ is the transition rate from the latent exposure state to the infected state; and $R(t)$ represents the nodes that have recovered and are temporarily immune to risk impacts.

$\frac{dS(t)}{dt} = -\beta S(t)I(t)$ describes the decline in the quantity of susceptible but healthy nodes $S(t)$ due to the contagion effect from infectious risk nodes $I(t)$. $\frac{dE(t)}{dt} = \beta S(t)I(t) - \sigma E(t)$ indicates

that after being exposed to risk shocks, part of the healthy nodes enters the latent exposed state $E(t)$, while part of the exposed nodes further converts into infectious risk nodes. $\frac{dI(t)}{dt} = \sigma E(t) - \gamma I(t)$ shows that exposed nodes convert to risk nodes at rate σ , and risk nodes exit the risk state at recovery rate γ . $\frac{dR(t)}{dt} = \gamma I(t)$ means that after recovery, risk nodes enter the recovered state $R(t)$.

Furthermore, the recovery capacity of nodes varies with market liquidity. Lower market liquidity makes it more difficult for distressed institutions to resume normal operations via financing or asset sales. Therefore, consistent with the setting of Cao and Feinstein, this paper specifies the recovery rate to be endogenously determined by the liquidity vector M , rather than being set as a fixed constant [12]. The aggregate market liquidity vector $M = (x + A^\top p - \bar{p})^+$ endogenously determines $\gamma(M)$. Substituting the endogenous recovery rate into the core contagion equation yields:

$$\frac{dI(t)}{dt} = \sigma E(t) - \gamma(M)I(t) \quad (4)$$

This integrated system of equations unifies multiple tail dependence associations, latent risk lag effects and the liquidity feedback from fire sales, and addresses the three isolated limitations inherent in the aforementioned relevant literature.

4. Analysis of risk contagion mechanisms in financial markets

4.1. Construction logic of multi-agent multi-layer networks

The multi-agent multi-layer network constructed in this paper takes commercial banks as the core intermediary nodes, incorporates two types of peripheral agents, namely real enterprises and financial asset portfolios, and forms three distinct but interconnected topological layers designed to capture major channels of risk transmission.

The first layer is the bank-enterprise credit network, where edges are defined by the bilateral credit lending relationships between banks and non-financial enterprises, and edge weights are measured by the scale of outstanding loans, which naturally forms heterogeneous connection intensity matching the characteristics of the real credit market: large enterprises maintain multi-bank lending correlations, while micro, small and medium-sized enterprises only form single or narrow credit connections, eventually generating node connectivity that is consistent with real credit data and follows the Pareto distribution. This layer mainly captures risk spillovers triggered by corporate debt default and the deterioration of credit quality.

The second layer is the interbank lending network, where edge weights are represented by the scale of overnight interbank lending and long-term financing exposure, and connections have significant asymmetric characteristics: large systemically important banks maintain extensive lending correlations with small and medium-sized financial institutions, while small banks have a very limited number of interbank trading counterparties. This layer is used to characterize the direct risk contagion among financial institutions through liquidity runs and interbank default chains.

The third layer is the bank-portfolio network, where edges are determined by the holding proportion of various types of assets in each bank's investment portfolio, and edge weights correspond to the asset holding proportion. Therefore, homogeneous assets jointly held by multiple banks will form dense cross-bank connection clusters. This layer mainly reflects the indirect risk transmission triggered by synchronous depreciation of asset prices and market fire sales.

After completing the construction of the three single-layer topologies, this paper introduces cross-layer correlation weights to quantify the cross-channel spillover intensity between layers, adopts extreme asset co-movement characteristics to adjust the connection strength of nodes between layers, and distinguishes the difference between strong tail risk correlation under market crash and weak correlation during stable periods. In addition, this paper applies a random matrix denoising tool to eliminate spurious correlations caused by short-term trading noise in raw asset data, and adopts a community detection algorithm to group assets with consistent risk fluctuation characteristics, enabling the network to accurately identify the clustered risk diffusion hubs formed by homogeneous asset portfolios.

The integrated three-layer multi-agent network obtained in this paper realizes the organic unification of credit correlation, interbank liquidity correlation and asset price correlation, providing a complete topological carrier for subsequent epidemic contagion simulation, and enabling the subsequent risk diffusion model to simultaneously capture direct interbank shocks, enterprise-derived indirect risks and systematic disturbances driven by asset depreciation.

4.2. Core influencing factors of financial risk diffusion

The transmission of cross-industry and cross-border systemic financial risks is jointly driven by three interrelated core mechanisms, which are rooted in network structure, dynamic temporal effects, and asset agglomeration characteristics respectively. Each factor has distinctly different economic implications for amplifying or mitigating risk shocks, and its theoretical foundation has been supported by existing network finance research [3, 10, 13, 14].

Network topology serves as the physical carrier for all risk transmission. Systems with financial interconnections exhibit a unique robust-fragile duality: sparse inter-institutional connections can disperse small negative shocks and stabilize market operation, while excessively dense bilateral risk exposures will form unobstructed risk transmission channels. Once a shock breaks through the critical threshold, it will trigger large-scale chain defaults [13]. Algebraic connectivity, a spectral graph index measuring the overall compactness of a network, can quantify such structural vulnerability. Empirical evidence from the European interbank market shows that the weaker the network connectivity, the longer the cycle required for market risk clearing [14].

Time-dependent lagged spillover chains dominate the rate of risk transmission. Static network snapshots cannot capture the sequential transmission order of risks across different financial sectors. In real markets, risks first impact shadow banking institutions that are more sensitive to asset volatility, and then transmit to commercial banks through short-term interbank lending. In a crisis state, stronger lagged tail correlation will form, compressing the potential accumulation period of implicit risks and accelerating systemic collapse [3].

Asset cluster heterogeneity determines the boundary of risk spillovers. Assets with consistent industry cycles and valuation logic naturally form contagion hubs. Within the same cluster, synchronous price fluctuations amplify risk resonance, among which technology asset portfolios have the strongest outward spillover effect. Even diversified allocation cannot suppress systemic risks, because the losses of the entire cluster will be transmitted to all associated financial entities [10]. In summary, topological characteristics determine the baseline capacity of risk transmission, time series control the contagion rate, and asset clusters delineate the spillover scope of financial shocks.

4.3. Risk management optimization mechanism

This paper constructs a three-tier systemic risk governance framework targeting three core diffusion channels, namely cross-level shock transmission, hub-driven contagion, and threshold-triggered systemic mutation, and further develops a full-cycle regulatory system covering micro-institutional constraints, macro network regulation and targeted dynamic early warning.

At the micro institutional level, differentiated credit and capital rules constitute the fundamental defense line to block cross-network risk spillovers. By raising the minimum capital adequacy ratio requirement and diversifying corporate credit allocation, regulatory authorities can weaken the correlation intensity among credit, interbank business and asset portfolios, and cut off the multi-channel shock transmission paths between heterogeneous market layers [5]. This regulatory logic reduces the sensitivity of individual banks to corporate defaults and asset depreciation shocks from the source.

From the perspective of macro networks, spectral topology regulation inhibits large-scale cascading risks by optimizing overall network connectivity. Targeted deleveraging policies for systemically important financial institutions can compress the connection weight of core hubs, reduce the algebraic connectivity index of the entire interbank market system, and confine shock diffusion within local institutional clusters [14]. This type of structural adjustment weakens the long-distance transmission capacity of extreme risks throughout the financial system.

In the dimension of targeted dynamic regulation, statistically calibrated node centrality indicators can accurately identify superspreaders of risk, avoiding misjudgment caused by uncorrected topological measurement noise [4]. Combined with the phase transition characteristics of financial networks, regulatory authorities can set clear risk intervention thresholds: launching preventive regulation before shocks reach the critical value can prevent the system from transitioning to a fragile, highly contagious state, and integrate structural optimization, differentiated institutional regulation and real-time threshold monitoring into a unified pre-crisis governance system [13, 15].

5. Conclusion

This paper constructs a temporal multi-layer SEIR financial contagion framework from three dimensions, namely network structure, propagation timing sequence and node importance, and attempts to embed the statistically tested Katz-Bonacich centrality into the key node identification process. Multi-layer topological structure, heterogeneous agent characteristics and the chain effect of time-lag shocks together constitute the core driving factors of cross-market contagion. Financial networks exhibit significant robust-fragile phase transition characteristics, while adequate bank capital buffers and diversified portfolios are inherent inhibitors of inter-layer risk spillovers. The multi-dimensional risk governance paradigm integrating topology optimization, differentiated prudential regulation and threshold early warning is proposed in this study, which is expected to constrain large-scale chain crises effectively. It is noteworthy that the effectiveness of this paradigm still needs further simulation and out-of-sample verification for empirical validation.

This study has two limitations in terms of research methodology. First, the liquidity parameter in the contagion model is set as a fixed exogenous value, and no endogenous feedback mechanism is constructed between asset fire sales and market liquidity, which leads to the model underestimating the substantial price impact under extreme market turmoil. Second, the spillover measurement framework in this paper adopts a linear model specification, which cannot capture the asymmetric risk spillover across different industries. This linear specification bias will distort risk estimation results during major crises and weaken the model's explanatory power for sudden systemic shocks.

Future research can extend this study along four critical dimensions. First, the continuous risk diffusion model can be extended to cross-border multinational banking systems to compare the differential effects of various financial regulatory policies across different economic jurisdictions. Second, subsequent studies should expand the research sample by including unlisted shadow banks and fintech institutions, so as to eliminate sample selection bias and reflect the real systemic risk profile more comprehensively. Third, high-dimensional time-varying econometric tools can be integrated with multi-layer contagion models to accurately capture the heterogeneous risk contagion characteristics across different industrial sectors. Fourth, spectral network indicators that measure overall connectivity can be introduced into dynamic early warning models to improve the timeliness and accuracy of systemic risk prediction.

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