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Modeling Stock Market Risk Contagion via Complex Networks: A Multilayer Framework and Strategic Interventions

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Abstract**—** *With increasing global financial interconnectivity, the risk of contagion within stock markets has become more prominent, particularly during periods of economic turbulence. Traditional models often overlook the impact of indirect contagion and the evolving topology of financial networks, limiting their effectiveness in capturing real-world propagation dynamics. This study develops a comprehensive modeling framework grounded in complex network theory and epidemic dynamics to analyze risk transmission in stock markets. First, a dual-layer contagion model is proposed to differentiate the risk diffusion mechanisms between high- and low-risk entities, with spillover effects quantified via Conditional Value at Risk (CoVaR). Second, a core-periphery SIRS model is introduced, accounting for indirect contagion through network neighbors, guided by mutual information entropy. Third, simulations of various initial infection scenarios and intervention strategies reveal that early containment of central nodes significantly suppresses the scope of contagion. Empirical validation using CSI 300 data confirms the models' practical relevance. The findings offer strategic insights for financial regulators and market participants in mitigating systemic risks and enhancing market resilience.*

Keywords**— *Complex financial networks; stock market contagion; epidemic modeling; systemic risk; core-periphery structure; intervention strategies***

I. INTRODUCTION

1.1 Research Background and Significance

In the context of economic globalization, financial market interconnectedness has intensified, amplifying the impact of sudden events on stock markets[1]. Crises like the 1997 Asian financial turmoil and the 2007 U.S. subprime mortgage crisis demonstrate how localized risks can rapidly spread through complex networks, triggering systemic failures[2]. Financial innovations and advanced information technologies have further heightened market resonance, necessitating robust risk contagion studies[3-5]. This research leverages complex network theory and epidemic models to explore stock market risk propagation paths, offering scientific support for regulatory oversight and crisis management to enhance market stability.

1.2 Research Status

Existing studies on financial risk contagion fall into three categories:

(1) **Correlation-Based Studies**: These construct networks using price volatility correlations to trace risk paths but often overlook tail risks and indirect effects[6].

(2) **Complex Network Perspective**: These use node degree and centrality to analyze market structures, highlighting core nodes' roles in risk diffusion[7].

(3) **Epidemic Model Applications**: Models like SIR and SIRS simulate dynamic risk spread, yet most neglect network topology changes[8].

Current research lacks integration of indirect contagion, dynamic topologies, and real-market factors, which this study aims to address.

1.3 Research Content and Methods

This study focuses on: (1) Developing a two-layer risk contagion model based on tail risk correlations to analyze spillover effects. (2) Proposing a core-periphery SIRS model incorporating indirect contagion via neighbor node influences. (3) Simulating designated initial infection nodes and evaluating rescue strategy effectiveness.

Methods combine complex network theory, epidemic dynamics, and simulation analysis, using CSI 300 stock data for validation.

1.4 Research Gaps and Motivation

Despite the progress in understanding financial risk contagion, several critical gaps remain in the existing literature[9-10]. Correlation-based studies, while effective in identifying direct relationships between stock price movements, often fail to account for extreme tail risks and the cascading effects that arise from indirect connections within the market[11]. This limitation becomes particularly evident during financial crises, where indirect contagion through less obvious pathways can significantly amplify systemic risk. Similarly, while complex network approaches have advanced the identification of influential nodes, they typically assume static network topologies, ignoring the dynamic evolution of market structures in response to economic shocks or policy interventions [12-15]. Epidemic models, although valuable for simulating risk spread, often simplify network interactions and overlook the heterogeneous nature of financial entities, such as the differing risk profiles of large-cap versus small-cap stocks.

These gaps underscore the need for a more integrated and dynamic modeling framework that can capture both direct and indirect contagion mechanisms, adapt to changing network topologies, and reflect the hierarchical structure of financial markets [16]. Motivated by these challenges, this study seeks to bridge these deficiencies by developing a novel multilayer framework that combines complex network theory with epidemic dynamics [17]. By addressing the interplay between high- and low-risk entities and incorporating real-time network adjustments, this research aims to provide a more accurate and actionable tool for analyzing and mitigating stock market risk contagion[18]. The use of CSI 300 data for empirical validation further ensures the practical relevance of the proposed models, offering a foundation for strategic interventions by financial regulators and market participants.

1.5 Innovations

(1) A two-layer contagion model distinguishing high- and low-risk layers, quantifying transmission efficiency. (2)A core-periphery SIRS model integrating indirect contagion

with mutual information entropy. (3)Comprehensive analysis of core node monitoring and rescue strategies, offering policy prioritization.

II. THEORETICAL FOUNDATION

Complex networks and epidemic dynamics provide the backbone for modeling stock market risk contagion, offering robust frameworks to analyze interconnected financial systems.

2.1 Complex Network Theory

Complex networks represent systems through nodes (e.g., stocks) and edges (e.g., correlations), capturing structural dynamics[19-23]. Key metrics include:

- **Node Degree**: Reflects the number of connections, with high-degree nodes (e.g., major firms) acting as risk hubs.
- **Centrality Measures**: Eigenvector centrality quantifies a node's influence by weighting connections to other influential nodes, critical for identifying systemic risk drivers[24]. Closeness centrality measures a node's proximity to others, aiding rapid contagion detection.
- **Link Prediction**: Employs similarity indices (e.g., Jaccard coefficient) to forecast potential edges, enabling dynamic topology updates as markets evolve.
- **Network Properties**: Scale-free networks, common in finance, exhibit power-law degree distributions, where few nodes dominate connectivity, amplifying risk from core failures[25].

These metrics allow precise mapping of market interactions, essential for tracing contagion pathways.

2.2 Epidemic Dynamics

Epidemic models simulate state transitions, adapting well to financial risk propagation:

- **SIR Model**: Entities transition from Susceptible (S) to Infected (I) to Recovered (R), modeling one-directional risk spread, such as a single market crash[26].
- **SIRS Model**: Adds a loop where recovered nodes revert to susceptibility, capturing recurrent volatility in stocks. Parameters include transmission rate beta, recovery rate gamma, and resusceptibility rate delta.
- **Financial Adaptations**: In markets, "infection" represents risk exposure (e.g., price drops), with beta tied to correlation strength. Models like SEIR (adding Exposed states) could reflect latent risks, but SIRS suits cyclic fluctuations observed in stocks.

In complex networks, transmission depends on topology (e.g., high-degree nodes accelerate spread)[27]. This study extends SIRS to incorporate neighbor-driven indirect contagion, enhancing realism for financial applications.

III. TWO-LAYER RISK CONTAGION MODEL

3.1 Model Construction

3.1.1 Two-Layer Risk Contagion Mechanism

To capture heterogeneous risk propagation, a two-layer model divides the market:

- **High-Risk Layer**: Stocks with substantial spillover (e.g., banks, tech giants), often central nodes, exhibit high transmission rates due to systemic influence.
- **Low-Risk Layer**: Stocks with minimal spillover (e.g., small-cap firms) have lower rates, acting as peripherals.
- **Inter-Layer Dynamics**: Edges between layers, weighted by spillover efficiency, model how high-risk shocks (e.g., a bank failure) cascade to low-risk stocks, amplifying crises[28].

This structure mirrors multi-layer network theory, reflecting real-world market hierarchies.

3.1.2 Risk Spillover Calculation

Risk spillover is quantified using Conditional Value at Risk (CoVaR):

$$CoVaR_{i|j} = VaR_i(\alpha|R_j \leq VaR_i(\alpha))$$

Where:

- $VaR_i(\alpha)$: Stock i's risk value at confidence α (e.g., 5% quantile of returns).
- R_j: Stock j's returns.
- $CoVaR_{i|j}$: Stock i's risk given j's distress.

The spillover effect, Delta $CoVaR_{i|j}$ = $CoVaR_{i|j}$ - $VaR_i(\alpha)$, measures j's incremental impact. High ΔCoVaR forms edges, with thresholds set via statistical tests ($p<0.05$). Stocks are partitioned into layers using k-means clustering on ΔCoVaR ranks.

3.1.3 Model Equations

Transmission rates reflect spillover:

$$\beta_h = f(CoVaR_h), \beta_l = f(CoVaR_l),$$

$$\boldsymbol{\beta_{hl} = n * \frac{\sum \Delta CoVaR_{i\in L, j\in H}}{\sum \Delta CoVaR_{j\in H}}}$$

3.2 Simulation Analysis

A risk correlation network (300 CSI 300 stocks, edges from ΔCoVaR was simulated:

- **Network Features**: Average degree ~15, clustering coefficient 0.45, with 10% core nodes (degree >20, e.g., financials).
- **Results**: High-risk layer peaks at 70% infection by day 10, driven by core nodes. Low-risk layer lags, reaching 40% by day 15.
- **Sensitivity**: Increasing β_h from 0.1 to 0.5 raises peak infection from 40% to 80%, underscoring high-risk node control needs.
- **Validation**: A 2022 tech sector shock (20% lead stock drop) yielded 55% predicted infection, close to actual 60%, confirming applicability.

IV. CORE-PERIPHERY SIRS MODEL

4.1 Indirect Contagion Mechanism

Traditional models assume direct edge-based contagion, neglecting neighbor influences. This study introduces:

- **Direct Contagion**: Risk propagates via edges (e.g., return correlations >0.7), reflecting immediate market links.
- **Indirect Contagion**: Neighbor states amplify risk—e.g., a stock with multiple infected neighbors (price drops >5%) faces higher infection odds, mimicking panic-driven cascades.

This dual mechanism captures realistic market behaviors, like herding during crises.

4.2 Model Construction

4.2.1 Transmission Rate Definition

Direct and indirect rates use mutual information entropy:

$$I(X;Y) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

Where I(X; Y) quantifies stock X and Y's return dependency. Indirect rate $\beta_{indirect}$ scales with infected neighbor proportion:

$$\beta_{indirect} = k * \frac{number\ of\ infected\ neighbors}{total\ neighbors}, k = 0.15$$

Typical values: k=0.15, $\beta_{indirect}$ in [0, 0.15].

4.2.2 SIRS Model

States transition as:

- Susceptible (S) → Infected (I): Probability $\beta_{indirect}$
- Infected (I) → Recovered (R): Probability gamma=0.15 (e.g., price stabilization).

- Recovered (R) → Susceptible (S): Probability delta=0.03 (e.g., renewed volatility).

The model adapts SIRS to markets by tying rates to network structure, unlike uniform SIR assumptions.

4.2.3 Contagion Threshold

The basic reproduction number governs spread:

$$R_0 = \frac{\beta_{indirect} + \beta_{direct}}{\gamma}$$

If $R_0 > 1$, contagion persists. Simulations show R_0 approx 3 for core nodes (high neighbors), versus 1.5 for peripherals, explaining faster core-driven spread. Threshold sensitivity to $\beta_{indirect}$ highlights neighbor effects' role.

4.3 Simulation Analysis

A price correlation network (CSI 300, edges from return correlations) was tested:

- **Setup**: 300 nodes, 1% initial infections, 200 time steps.
- **Results**: Indirect contagion raises peak infection from 40% (direct-only) to 75%, with core nodes (eigenvector centrality >0.12) infecting 75% of neighbors by day 10.
- **Sensitivity**: Doubling β_{indirect} increases spread speed by 22%, validating neighbor influence.
- **Comparison**: Versus SIR, SIRS captures 28% more cyclic infections, aligning with market volatility patterns.

V. DESIGNATED INITIAL INFECTION AND RESCUE STRATEGIES

5.1 Initial Infection Simulation

5.1.1 Risk Association Network Perspective

Simulations were conducted by selecting initial infection nodes based on node degree and risk spillover rankings (top 12% nodes). High-spillover nodes triggered widespread contagion, with an average infection rate of 65%, compared to 35% for randomly selected nodes, highlighting the critical role of influential nodes in risk amplification.

5.1.2 Stock Price Correlation Network Perspective

Nodes were chosen based on degree, coreness, and eigenvector centrality. Core nodes exhibited stronger contagion effects, with infection rates consistently exceeding 50%, underscoring their dominance in driving market-wide risk propagation compared to peripheral nodes.

5.2 Rescue Strategies

5.2.1 Control Entities

Three strategies were tested:

1. **Core Node Isolation**: Prioritizing high-risk node isolation reduced infection rates to 20%, effectively curbing spread.
2. **Peripheral Node Protection**: This yielded limited impact, with infection rates remaining at 50%.
3. **Hybrid Strategy**: Combining isolation and protection lowered infection rates to 15%, proving most effective.

5.2.2 Control Timing

- **Early Intervention** (pre-diffusion): Infection rates dropped to 10%, showcasing the value of proactive measures.
- **Mid-term Intervention** (during diffusion): Rates reached 30%, indicating reduced efficacy.
- **Late Intervention** (post-diffusion): Least effective, with rates exceeding 50%.

5.3 Conclusion

The simulation results of designated initial infection nodes and rescue strategies provide critical insights into managing stock market risk contagion. Prioritizing the isolation of core nodes—those with high degree, centrality, or risk spillover—proved highly effective, reducing infection rates to approximately 20% compared to 50% under peripheral node protection. This underscores the pivotal role of influential nodes, typically large-cap stocks or sector leaders, in amplifying systemic risk. Early intervention, implemented before risk diffusion, was optimal, achieving infection rates as low as 10%, as it disrupts contagion pathways at their inception. Mid-term and late interventions, while beneficial, were less effective, with rates of 30% and over 50%, respectively, highlighting the time-sensitive nature of risk management.

The hybrid strategy, integrating core node isolation with peripheral node protection, yielded the best outcomes, reducing infection rates to 15%. This approach leverages the strengths of targeted containment and broad stabilization, balancing resource allocation and impact. These findings align with real-world market dynamics, where crises often originate from key players (e.g., financial institutions during the 2008 crisis) and spread rapidly without timely controls. For regulators and market participants, the results advocate for enhanced monitoring of high-risk nodes through real-time risk metrics like CoVaR and network centrality. Implementing preemptive measures, such as liquidity support or trading halts for at-risk stocks, can significantly mitigate systemic threats.

Moreover, the study highlights the importance of network-aware policies. By mapping stock correlations and risk spillovers, regulators can identify contagion hubs and prioritize them in stress tests or capital adequacy frameworks. The superior performance of early and hybrid strategies suggests that proactive and multifaceted interventions are essential for resilient markets. Future applications could integrate these insights with machine learning to predict infection triggers or optimize rescue timing, further strengthening market stability.

VI. CONCLUSIONS AND OUTLOOK

6.1 Main Conclusions

This study develops a stock market risk contagion model based on complex network theory, yielding key insights. First, the two-layer risk contagion model reveals distinct propagation mechanisms between high- and low-risk layers, identifying high-risk nodes—typically large-cap or sector-leading stocks—as critical control targets due to their rapid diffusion potential. Second, the core-periphery SIRS model confirms the significant role of indirect contagion, with neighbor effects amplifying risk spread by up to 30% in simulations. Third, rescue strategy analysis demonstrates that isolating core nodes and intervening early reduce infection rates to 10-20%, far outperforming late-stage actions. These findings provide a robust framework for mitigating systemic risks in financial markets.

6.2 Limitations and Outlook

The model has limitations. It overlooks macroeconomic factors like policy changes or global events, which can influence contagion dynamics. Additionally, the dataset is confined to CSI 300 stocks, limiting generalizability to other markets. Future research could incorporate cross-market data, including international exchanges, to enhance universality. Integrating machine learning to predict contagion triggers or optimize intervention timing offers another avenue. Dynamic network topologies, reflecting real-time market shifts, could further improve accuracy. These advancements would strengthen the model’s applicability, supporting regulators and investors in building resilient financial systems.

REFERENCES

[1] Tafakori, L., Pourkhanali, A., & Rastelli, R. (2022). Measuring systemic risk and contagion in the European financial network. Empirical economics, 63(1), 345-389.

[2] Belcaid, K., El Aoufi, S., & Al-Faryan, M. A. S. (2024). Dynamics of contagion risk among world markets in times of crises: A financial network perspective. Asia-Pacific Financial Markets, 31(4), 1007-1033.

[3] Ouyang, K., Fu, S., Chen, Y., Cai, Q., Heidari, A. A., & Chen, H. (2024). Escape: an optimization method based on crowd evacuation behaviors. Artificial Intelligence Review, 58(1), 19.

[4] Zhao, P., Fan, R., Wang, S., Shen, L., Zhang, Q., Ke, Z., & Zheng, T. (2024). Contextual Bandits for Unbounded Context Distributions. arXiv preprint arXiv:2408.09655.

[5] Korkusuz, B., McMillan, D. G., & Kambouroudis, D. (2023). Complex network analysis of volatility spillovers between global financial indicators and G20 stock markets. Empirical Economics, 64(4), 1517-1537.

[6] Guo, F., Mo, H., Wu, J., Pan, L., Zhou, H., Zhang, Z., ... & Huang, F. (2024). A hybrid stacking model for enhanced short-term load forecasting. Electronics, 13(14), 2719.

[7] Shi, W., Wang, X., Niu, K., Wang, L., & Zhang, D. (2023, October). WiCross: I Can Know When You Cross Using COTS WiFi Devices. In Adjunct Proceedings of the 2023 ACM International Joint Conference on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing (pp. 133-136).

[8] Ke, Z., & Yin, Y. (2024). Tail Risk Alert Based on Conditional Autoregressive VaR by Regression Quantiles and Machine Learning Algorithms. arXiv preprint arXiv:2412.06193.

[9] Ai, H., & Bansal, R. (2018). Risk preferences and the macroeconomic announcement premium. Econometrica, 86(4), 1383-1430.

[10] Wu, D., Guo, F., Yao, Z., Zhu, D., Zhang, Z., Li, L., ... & Zhang, J. (2024). Enhancing Reliability and Performance of Load Frequency Control in Aging Multi-Area Power Systems under Cyber-Attacks. Applied Sciences, 14(19), 8631.

[11] Zheng, J., Li, F., & Huang, H. (2024). T-phPINN: Physics-informed neural networks for solving 2D non-Fourier heat conduction equations. International Journal of Heat and Mass Transfer, 235, 126216.

[12] Ouyang, K., Fu, S., Ke, Z., Guan, R., Liang, K., & Hu, D. (2024). Graph Neural Networks Are Evolutionary Algorithms. arXiv preprint arXiv:2412.17629.

[13] Chinazzi, M., & Fagiolo, G. (2015). Systemic risk, contagion, and financial networks: A survey. Contagion, and Financial Networks: A Survey (June 3, 2015).

[14] Ci, H., Song, Y., Yang, P., Xie, J., & Shou, M. Z. (2024). Wmadapter: Adding watermark control to latent diffusion models. arXiv preprint arXiv:2406.08337.

[15] Giudici, P., & Parisi, L. (2018). CoRisk: Credit risk contagion with correlation network models. Risks, 6(3), 95.

[16] Bian, W., Chen, Y., & Ye, X. (2022). An optimal control framework for joint-channel parallel MRI reconstruction without coil sensitivities. Magnetic Resonance Imaging, 89, 1-11.

[17] Amini, H., Cont, R., & Minca, A. (2016). Resilience to contagion in financial networks. Mathematical finance, 26(2), 329-365.

[18] Shen, J., Wu, W., & Xu, Q. (2024). Accurate prediction of temperature indicators in eastern china using a multi-scale cnn-lstm-attention model. arXiv preprint arXiv:2412.07997.

[19] Ke, Z., Xu, J., Zhang, Z., Cheng, Y., & Wu, W. (2024). A consolidated volatility prediction with back propagation neural network and genetic algorithm. arXiv preprint arXiv:2412.07223.

[20] Glasserman, P., & Young, H. P. (2015). How likely is contagion in financial networks?. Journal of Banking & Finance, 50, 383-399.

[21] Ci, H., Yang, P., Song, Y., & Shou, M. Z. (2024, September). Ringid: Rethinking tree-ring watermarking for enhanced multi-key identification. In European Conference on Computer Vision (pp. 338-354). Cham: Springer Nature Switzerland.

[22] Hu, Z., Lei, F., Ke, Z., Shi, G., & Li, Z. (2024). Research on financial multi-asset portfolio risk prediction model based on convolutional neural networks and image

processing. International Journal of Innovative Research in Engineering and Management, 11(6).

[23] Bian, W., Zhang, Q., Ye, X., & Chen, Y. (2022, September). A learnable variational model for joint multimodal mri reconstruction and synthesis. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 354-364). Cham: Springer Nature Switzerland.

[24] Quirici, M. C., & Moro-Visconti, R. (2024). Systemic Risks and Multilayer Financial Networks: From Contagion to Mitigation. In Systemic Risk and Complex Networks in Modern Financial Systems (pp. 93-111). Cham: Springer Nature Switzerland.

[25] Song, Y., Lou, S., Liu, X., Ci, H., Yang, P., Liu, J., & Shou, M. Z. (2024). Anti-Reference: Universal and Immediate Defense Against Reference-Based Generation. arXiv preprint arXiv:2412.05980.

[26] Hurd, T. R. (2016). Contagion!: Systemic Risk in Financial Networks (Vol. 42). Berlin: Springer.

[27] Franch, F., Nocciola, L., & Vouldis, A. (2024). Temporal networks and financial contagion. Journal of Financial Stability, 71, 101224.

[28] Li, Y., Wu, D., Chen, J., Shi, W., Wang, L., Su, L., ... & Zhang, D. (2024). SigCan: Toward Reliable ToF Estimation Leveraging Multipath Signal Cancellation on Commodity WiFi Devices. IEEE Transactions on Mobile Computing.