Journal of Financial Stability

How Dynamic Industry Sector Linkage Drive Risk Contagion: Evidence from China's Bayesian Time-Varying Complex Network

--Manuscript Draft--

Manuscript Number:	JFS-D-24-01142
Article Type:	Research Paper
Keywords:	Sector Linkage; Risk Contagion Mechanism; Time-Varying Complex Network; DCC-GARCH-Network CoVaR
Corresponding Author:	Ning Zhao Dongbei University of Finance and Economics Dalian, CHINA
First Author:	Ning Zhao
Order of Authors:	Ning Zhao
	Zhongxing Ren
	Zhenshuang Wang
Abstract:	Cross-industry financial risk contagion represents the most damaging phase to the real economy during a crisis, as understanding its diffusion characteristics and underlying mechanisms is crucial to determining the success of an economy in combating the crisis. Our study employs a time-varying parameter vector auto-regression (TVP-VAR) model to construct a complex network of Chinese industries, aiming to investigate the impact of dynamic network structures and their formation mechanisms on cross-industry risk contagion during crises. We selected four typical shock periods over the past decade (2014–2024) to construct a network using the Wind Level-1 industry indices of the Chinese A-share market. In the dynamic network, we calculated the DCC-GARCH-network CoVaR to measure network risk contagion, identifying four periods of significant risk surges. The TVP-VAR dynamic correlation coefficients exhibited a trend of gradual increase. Furthermore, mechanism analysis revealed that cross-industry linkages positively drive risk contagion, with direct linkage structures playing a dominant role in this process. The structure, characterized by multi-node consistent risk outputs, can cause short-term risk surges in overall network. Moreover, it amplifies the asymmetry of risk contagion by enhancing the vulnerability of cyclical and financial sectors, which are more sensitive to fundamental factors. The findings of this study on network structure analysis in continuous time provide new evidence for designing more targeted risk early-warning mechanisms and exposure node risk control strategies in China and other emerging market economies.
Suggested Reviewers:	Tim Zhang The University of Texas at San Antonio Tim.zhang@utsa.edu
	Chia-Hung Chuang University of North Dakota chiahung.chuang@und.edu

Dr. Ning Zhao
Associate Professor in Risk Management
School of Finance
Dongbei University of Finance and Economics
Shahekou District, Dalian, P.R.China, 116025
Email: ning.zhao@msn.com

4th December, 2024.

Dear Editorial Board,

We are pleased to submit the manuscript entitled, "*How Dynamic linkage Drive Chinese Financial Risk Contagion: Evidence from Bayesian Time-Varying Complex Network*" for your review and possible publication in Journal of Financial Stability. This manuscript is our original unpublished work.

Cross-industry financial risk contagion often represents the most destructive phase of a financial crisis. While excessive connectivity is commonly viewed as a cause of financial risk contagion, our study goes further to explore how evolving network structures and their formation mechanisms shape cross-industry risk contagion during economic turbulence.

We focus on four significant shock periods from 2014 to 2024, using the Wind Level-1 industry indices of the Chinese A-share market. In our analysis, we utilize the DCC-GARCH-network CoVaR to quantify risk contagion within the network, identifying four distinct periods of risk surges. The TVP-VAR model results highlight its ability to capture the network's dynamic characteristics, revealing continuous time fluctuations and a clear trend of increasing interconnectedness.

The mechanism analysis uncovers that direct cross-industry linkages play a pivotal role in driving risk contagion in China. The network structure, characterized by multi-node consistent risk outputs, can induce short-term risk surges throughout the network. Notably, this structure exacerbates the asymmetry of risk contagion, especially by heightening the vulnerabilities of cyclical and financial sectors, which are more sensitive to fundamental economic factors.

Our study explores financial contagion dynamics, providing insights for targeted early-warning systems and risk control strategies in China and other emerging markets. As the world's largest emerging market, China's industry network dynamics and contagion mechanisms are critical to both domestic and global economic stability. By analyzing cross-industry contagion, our findings contribute to understanding global market interactions and shaping policies to mitigate systemic risks.

Thank you for considering our manuscript. We look forward to your feedback and hope for the opportunity to contribute to the ongoing scholarly discourse on financial risk contagion.

Should you need to contact us, please use the email address provided as above.

Thank you very much.

Sincerely yours,

Ning Zhao

Highlights

- A time-varying complex network is constructed to capture continuous-time cross-industry linkages.
- The DCC-GARCH-network CoVaR is used to measure network risk contagion.
- Continuous-time cross-industry linkages impact network risk contagion through direct and indirect linkage structures.
- The direct-linkage structure dominates cross-industry risk contagion in China.
- Finance and cyclical sectors contribute more to risk contagion within the direct-linkage structure.

How Dynamic Industry Sector Linkage Drive Risk Contagion: Evidence from China's Bayesian Time-Varying Complex Network

Ning Zhao, Ph.D.[1]

[1]Associate Professor, School of Finance, Dongbei University of Finance and Economics, Dalian, China, 116025. E-mail: ningzhao@dufe.edu.cn

Zhongxing Ren[2]

[2]Master's student, China School of Banking and Finance, University of International Business and Economics, Beijing, 100029. E-mail: renzhongxing2002@163.com

Zhenshuang Wang Ph.D.[3]

[3]School of Investment and Construction Management, Dongbei University of Finance and Economics, Dalian, China, 116025. E-mail: zswang@dufe.edu.cn **(Corresponding author)**.

Conflict of interest disclosure: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability statement: Data and algorithm presented in this study were available on request from the corresponding author.

Funding statement: This research was supported by National Natural Science Foundation of China (No. 72001035) and the China Ministry of Education Planning Fund Project (No. 24YJAZH148).

How Dynamic Industry Sector Linkage Drive Risk Contagion: Evidence from China's Bayesian Time-Varying Complex Network

Abstract

Cross-industry financial risk contagion represents the most damaging phase to the real economy during a crisis, as understanding its diffusion characteristics and underlying mechanisms is crucial to determining the success of an economy in combating the crisis. Our study employs a time-varying parameter vector auto-regression (TVP-VAR) model to construct a complex network of Chinese industries, aiming to investigate the impact of dynamic network structures and their formation mechanisms on cross-industry risk contagion during crises. We selected four typical shock periods over the past decade (2014–2024) to construct a network using the Wind Level-1 industry indices of the Chinese A-share market. In the dynamic network, we calculated the DCC-GARCH-network CoVaR to measure network risk contagion, identifying four periods of significant risk surges. The TVP-VAR dynamic correlation coefficients exhibited a trend of gradual increase. Furthermore, mechanism analysis revealed that cross-industry linkages positively drive risk contagion, with direct linkage structures playing a dominant role in this process. The structure, characterized by multi-node consistent risk outputs, can cause short-term risk surges in overall network. Moreover, it amplifies the asymmetry of risk contagion by enhancing the vulnerability of cyclical and financial sectors, which are more sensitive to fundamental factors. The findings of this study on network structure analysis in continuous time provide new evidence for designing more targeted risk early-warning mechanisms and exposure node risk control strategies in China and other emerging market economies.

Key words: Sector Linkage; Risk Contagion Mechanism; Time-Varying Complex Network; DCC-GARCH-Network CoVaR

I. Introduction

Whether during the subprime mortgage crisis or the European debt crisis, both researchers and regulators have identified that cross-industry contagion poses severe negative impacts on the economy. (Adrian & Brunnermeier, 2016; Kapinos et al., 2022; Oh & Patton, 2017; Zedda &

Cannas, 2020). In recent years, this contagion has shifted from a past trend of 'single, localized, small-scale, phased changes' to a more complex, globalized, large-scale, and real-time nature.(Zhou & Liu, 2023). Cross-industry risk contagion stems from the interconnections between industries, but the relationship is not simply causal(Nivorozhkin & Chondrogiannis, 2022). As the financialization of industries deepens, a time-varying information exchange network gradually forms between sectors, where the structural characteristics of the network play a significant role in shaping the propagation of risk. Grant & Yung (2021) suggest that a decentralized network structure can mitigate risk contagion arising from cross-industry connections, while most studies agree that network transmission structures, characterized by excessive connections, facilitate risk contagion, and that these structures are dynamic (Paddrik et al., 2020; Xu et al., 2022).

Furthermore, in network transmission structures, the characteristics of nodes and edges can lead to either direct or indirect transmission of risk contagion. Directly transmission networks exhibit a co-movement between the industries, often accompanied by multiple risk exposures, which accelerates the contagion process, though it tends to be concentrated around certain risk-exposed nodes. In contrast, networks dominated by indirect linkages rely on intermediary nodes for information transmission between industries; this results in more sustained risk contagion with a wider diffusion range(Bardoscia et al., 2021). This differentiation directly influences the scale and speed of risk contagion, which, as evident, has significant implications for the formulation of risk control strategies. However, existing research primarily offers theoretical analysis and lacks sufficient empirical evidence. Most studies focus on demonstrating how strong interconnections between banks and other financial sectors drive contagion (Li et al., 2023; Nivorozhkin & Chondrogiannis, 2022; Paltalidis et al., 2015) rather than exploring how differences in network structures influence the contagion process.

China, as a globally recognized emerging market, has played an increasingly significant role in the world economy over the past decade, both in its industries and financial markets. Understanding the dynamic characteristics of China's cross-industry linkages and their contagion mechanisms is not only critical for shaping effective risk management strategies in an increasingly interconnected global market but also provides valuable insights for the development trajectories of other emerging economies.

Our study constructs the cross-industry network using the Wind Level-1 Industry Indices from

China's A-share market. To preserve the dynamic nature of the network structure, we estimate linkages using the TVP-VAR model. Additionally, we employ the DCC-GARCH-network CoVaR to capture the network risk contagion and investigate how the network structure influences the mechanisms of risk contagion. Our study offers the following contributions.

First, our study empirically demonstrates the dynamic characteristics of cross-industry networks in China and their role in driving cross-industry risk contagion. We utilize daily stock market data from 2014 to 2024, capturing four representative market shock events. Unlike networks constructed using quarterly financial data, our dynamic network based on daily data offers a finer resolution, allowing for a better capture of short-term market fluctuations. Instead of relying on traditional rolling window estimation methods, we employ a Bayesian TVP-VAR model to estimate the adjacency matrix of the time-varying network. This approach enables the construction of a directed and weighted dynamic complex network from the perspective of dynamic network evolution. By integrating both historical information and real-time market conditions, this method overcomes the limitations of rolling window techniques, such as the sensitivity to window selection at specific time points. Moreover, it addresses issues related to outliers and missing data, ensuring more robust and reliable network estimation(Choi, 2023; D. Wen & Wang, 2021).

We further examine the moderating mechanisms of the topological structure in the risk contagion. Unlike many network studies that primarily identify key nodes, we distinguish between the moderating effects of direct and indirect linkages on risk contagion. This approach reveals unique characteristics of China's cross-industry networks, including high market sensitivity, short buffering periods, and a dominant direct-linkage pattern that leads to multi-node risk exposure. Importantly, these findings remain robust even after addressing potential endogeneity issues arising from reverse causality and omitted variables. Building on the overall network analysis, we segment industry attributes to investigate variations in risk contagion mechanisms. Our results confirm that cyclical and financial sectors occupy central positions in the network and exhibit stronger direct contagion capabilities. Furthermore, by categorizing periods of market crises, we find that strengthened interconnectedness significantly amplify risk contagion during crises. However, the properties of direct linkages and risk transmission characteristics remain consistent across the entire period.

Overall, our findings contribute to a deeper understanding of the risks associated with industrial economic integration and the insights offered by cross-industry network structures for shock resistance and risk management strategies. This study provides valuable guidance not only for shaping China's risk monitoring policies but also for other emerging markets seeking pathways for sustainable industrial development. More importantly, as industrial transformations accelerate and global industrial cooperation deepens, the traditional approach of minimizing excessive connections to prevent contagion will face increasing challenges. The perspective of network structures offers a novel approach to designing dynamic risk mitigation strategies in an increasingly interconnected global economy. Furthermore, in volatile and highly interconnected financial markets, our conclusions from the dynamic connectedness structure perspective provide valuable evidence for investors to design more resilient portfolio strategies.

II. Literature Review and Research Hypotheses

After the 2008 subprime mortgage crisis, the academic research begin to recognize systemic risk as a negative externality manifested in the widespread diffusion within the economic system(Adrian & Brunnermeier, 2016). Systemic risk is composed of specific risks and risk contagion (Kapinos et al., 2022; Zedda & Cannas, 2020). The core of market regulation shifted from the idea of "too big to fail" to "too interconnected to fail" (Markose et al., 2012). And the academic research has increasingly focused on the role of interconnections in financial markets in the generation and contagion of systemic risk.

This line of research has primarily evolved in two stages. The first stage is characterized by the conditional Value-at-Risk (CoVaR), Adrian and Brunnermeier (2016) pioneered the design of CoVaR, using tail dependence to measure this negative externality. The method considers the returns of individual assets and macro-market conditions as separate conditions, assessing the magnitude or contribution level of systemic risk. Following CoVaR, other measures that characterize individual risk features, such as MES (Acharya et al., 2017) and SRISK (Brownlees & Engle, 2016), were introduced. However, these studies share similar characteristics with CoVaR and do not focus on the interactivity between specific sectors or the complex contagion process of risk transmission.

With the increasing demand for precision in risk control by regulatory authorities, the second stage of research has gradually shifted towards network analysis perspectives. In this approach, nodes and edges are used to describe the interconnected relationships between multiple entities (Bardoscia et al., 2021; Haldane, 2009). There are two primary data sources for network analysis in this context: one is the financial data, where networks are constructed based on the transaction record and balance sheet, typically using simulation methods to measure the correlations and risk contagion processes between each nodes (Paltalidis et al., 2015). For example, Tanna et al. (2019) used inter-bank balance sheet data to construct a "core-periphery" network structure, finding that an increase in the number of core banks helps strengthen the network's resilience to risk contagion. But the quarterly balance sheet data can’t reflect all market information in time and may lead to a delayed risk measurement result (Fan et al., 2021). The other data source comes from market information, where real-time market trading prices are used to characterize the interconnected network, thus meeting the demand for real-time and high-frequency correlations (Gong et al., 2019; Wang et al., 2018). Research on market information networks has evolved from static to dynamic models. Representative static networks include Granger causality networks (Billio et al., 2012) and volatility networks (Wang et al., 2021). And because of the traditional static complex networks are unable to accommodate the real-time structural changes caused by market shocks. The rolling window method is widely used to construct dynamic networks, connecting multiple static networks over time to display network estimation results for different time intervals. Wang et al. (2017) calculate time-varying in-degrees and out-degrees of nodes and identifying risk contributors and recipients during various shock periods. Furtherly, Wang et al. (2018) apply TENETs networks to identify Chinese financial institutions with macro and micro-driven roles during multiple tail events. (Fan et al., 2021) combined the minimum spanning tree (MST) model with the rolling window method to construct a dynamic correlation network of the Chinese stock market, discovering that the average path length of the correlation network effectively identifies financial crisis events. Contrast with the rolling-window method, the time-varying parameter estimation method is gradually step into the interconnectedness measurement. Overcoming the subjective errors in window width selection and addressing data loss issues in rolling window methods, thus improving accuracy and robustness (Wan et al., 2024). Geraci and Gnabo (2018) were the first to use the TVP-VAR estimation method to construct dynamic adjacency matrices for identifying risk contributors during financial crises. (Zhou & Liu, 2023) furtherly used TVP-VAR combined with variance decomposition to construct a directed and weighted risk spillover network for global stock markets, discovering that the Asia-Pacific markets exhibited the highest risk-taking and structural changes during the COVID-19 crisis. Research in the second stage generally focuses on the qualitative identification of "importance" within the network through ranking the network indicators., but without considering the interactions within complex networks. And the quantitative relationship between network linkages and risk contagion still deserves further discussion.

In a dynamic financial network, risk contagion is the process by which the idiosyncratic risk of individual nodes spreads to the broader network. Increased network connectivity may enhance the homogeneity of internal nodes, resulting in synchronized co-movements of asset prices among nodes. Within networks of varying structures, the influence of such inter-node interactions differs; however, there is currently no consensus on whether the time-varying interconnected features of these networks amplify risk contagion or serve to disperse risk. Bardoscia et al. (2021) firstly examine the dual roles of financial network connectivity in either dispersing or intensifying risk, which depending on the nature of the shock and changes in network topology. On one hand, Grant and Yung (2021) investigate the global large-scale inter-firm financial network, found that highly connected networks exhibited risk-dispersing effects, shortening the duration of loss periods and reducing the magnitude of losses during shocks. On the other hand, network nodes may also exhibit similar risk exposures, leading to increased sensitivity to shocks and risk amplification effects, as highlighted by (Amini & Minca, 2016). Paddrik et al. (2020) explored the U.S. CDS network and found that excessive counterparty exposures induced chain defaults. Similar risk exposures can be magnified, with network connections acting as contagion pathways that propagate shocks across the network and enhance risk contagion (Klages-Mundt & Minca, 2020). Buraschi and Tebaldi (2023) further proposed that networks may exist in different states: a sub-critical state can help disperse risk across the network, while an over-connected super-critical state breaks down diversification benefits, leading to a significant increase in risk premiums. Thus, risk contagion is the process by which the idiosyncratic risks of micro-level nodes diffuse on a macro scale. The impact of connectivity on risk contagion varies depending on the sample period and the network environment formed by different research objects, and a consensus remains elusive. Therefore, to address which mechanism: *amplification* or *dispersion* dominates in the context of risk contagion within China's industry sector network, we propose Research Hypothesis 1:

H1a: The strengthening of sectoral interconnectedness promotes risk contagion, having a positive amplifying effect.

H1b: The strengthening of sectoral interconnectedness will mitigate risk contagion, having a negative suppressing and diversification effect.

On this basis, we further examine the internal topological structure changes of the network to understand the mechanism of risk contagion. The network topology structure affects the overall stability of the network. (Markose et al., 2012) find that nodes with high centrality and connectivity in the U.S. CDS network act as “super-spreaders” of risk, with contagion being highly concentrated and localized among closely connected nodes. Gong et al. (2019) demonstrated that node characteristic indicators, extracted through principal component analysis of indirect association metrics like eigenvector centrality and adjacency centrality, are effective in predicting systemic risk. S. Wen et al. (2023) found that in the Network CoVaR network of European financial institutions, most nodes ranked highly by eigenvector centrality were fintech institutions, which play a key role in indirect associations within the network. Unlike calculations based on direct connectivity, Kitsak et al. (2010) using simulation method to contrasted direct and indirect linkages structures and found that intermediary nodes with higher indirect connectivity demonstrate greater information transmission efficiency. Under the influence of direct associations, multi-node networks exhibit synchronized movement, prompting rapid short-term system changes; whereas with indirect linkages dominance, system state changes exhibit long-term and sustained characteristics. The two patterns thus play different leading roles across various network structures (Li et al., 2023). In financial networks dominated by direct linkages, risk contagion increases rapidly in the short term, with multiple nodes showing simultaneous risk exposure. Conversely, under indirect linkages pattern, while common risk exposure is relatively lower, sustained risk transmission persists among nodes, needing long-term regulatory risk control strategies. Authorities should design policies to intercept indirect risk contagion and prevent its widespread network propagation. Understanding the regulatory effects of different network topologies on association is crucial for policy formulation and the design of risk management mechanisms by regulatory agencies. We select adjacency centrality, betweenness centrality, and eigenvector centrality to represent indirect association measures, while in-degree and out-degree centrality are chosen as metrics for direct linkages. These are used as moderating variables to explore which form is predominant in the contagion of risks between industries in China, thereby providing regulatory agencies with refined risk control measures and policy frameworks. Based on this, we proposed Hypothesis as follows:

H2a: Direct linkages promote systemic risk contagion, driving the rapid surge or decline of contagion during crisis periods.

H2b: Indirect linkages suppress the systemic risk contagion, showing as gradual accumulation or gradual weakening the contagion during crisis periods.

III. Methodology

3.1 Time-varying linkages network

To construct the dynamic inter-industry correlation network for the Chinese stock market, this study employs the TVP-VAR model to estimate the time-varying coefficient matrix of industry index returns, which serves as the dynamic adjacency matrix reflecting the co-movement of asset prices across industries (Geraci & Gnabo, 2018). Let $G_t(E_t, V)$ represent the network structure generated at time t, where V is the set of nodes and E_t is the set of edges which presented the directed linkages at time t. E_t derived from the time-varying coefficient matrix estimated by the TVP-VAR model. The time-varying coefficients are updated using the Bayesian posterior distribution generated through the MCMC method, based on Bayes' theorem, as described by Nakajima (2011); Nakajima et al. (2011). This allows for the construction of the dynamic network and the calculation of its corresponding network features. In the vector autoregressive model (1), y_t is a k-dimensional vector, A, F are $\mathrm{k} \times \mathrm{k}$ coefficient matrices, and $\epsilon_t \sim N(0, \Omega)$ represents the error term.

$$Ay_t = F_1 y_{t-1} + \cdots + F_s y_{t-s} + \epsilon_t, \quad t = s+1, \cdots, n \tag{1}$$

Applying the Cholesky decomposition to the covariance matrix Ω the contemporaneous variables:

$$\Omega = A^{-1} H \left(A^{-1}\right)' \tag{2}$$

A is a lower-triangular matrix represent to the simultaneous relations of the structural shock; H is the matrix of stochastic volatility.

$$A = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ a_{21} & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ a_{k1} & \cdots & a_{k,k-1} & 1 \end{pmatrix} \qquad H = \begin{pmatrix} h_1 & 0 & \cdots & 0 \\ 0 & \ddots & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & h_k \end{pmatrix} \tag{3}$$

Thus, Eq(1) equals to:

$$y_t = B_1 y_{t-1} + \cdots + B_s y_{t-s} + A^{-1} H \varepsilon_t, \quad \varepsilon_t \sim N(0, I_k) \tag{4}$$

B is the parameter matrix, for any lag order $s = 1, \cdots S$, $B_s = A^{-1} F_s$. h_k is the standard deviation of the structural shock. Staking the elements in the rows of the B_s to form $k^2 s \times 1$ dimensional matrix β. Set $X = I_k \otimes (y'_{t-1}, \cdots, y'_{t-s})$:

$$y_t = X\beta + A^{-1} H \varepsilon_t \tag{5}$$

And we then consider the time-varying parameters to capture the dynamic linkages between nodes as Eq (6):

$$y_t = X_t \beta_t + A_t^{-1} H_t \varepsilon_t \tag{6}$$

Both β_t, A_t and H_t are the time-varying coefficient matrix. α_t is the stacked vector of the lower-triangular elements in A_t. for $k = 1, \ldots, K$ and $t = s+1, \ldots, n$, we define $h_k = log\, \sigma_k^2$: $h_t = (h_{1t}, \ldots, h_{kt})'$. Where h_k is a stationary process. And in order to capture the possible gradual (or sudden) structural change in stochastic volatility, we assume a random-walk process for the time-varying parameters.

$$\begin{aligned} \beta_{t+1} &= \beta_t + \mu_{\beta t}, \\ \alpha_{t+1} &= \alpha_t + \mu_{\alpha t}, \\ h_{t+1} &= h_t + \mu_{ht}, \end{aligned} \quad \begin{pmatrix} \varepsilon_t \\ \mu_{\beta t} \\ \mu_{\alpha t} \\ \mu_{ht} \end{pmatrix} \sim N \left(0, \begin{pmatrix} I_n & 0 & \cdots & 0 \\ 0 & \Sigma_\beta & \ddots & \vdots \\ \vdots & \ddots & \Sigma_\alpha & 0 \\ 0 & \cdots & 0 & \Sigma_h \end{pmatrix} \right) \tag{7}$$

I_k is the identity matrix, Σ_β, Σ_α, Σ_h are all diagonal matrices. We assume that the time-varying parameters β_t, α_t, h_t are independent with each other, and the rest parameters follow the distribution as $\beta_{s+1} \sim N(\mu_{\beta 0}, \Sigma_{\beta 0})$, $\alpha_{s+1} \sim N(\mu_{\alpha 0}, \Sigma_{\alpha 0})$, $h_{s+1} \sim N(\mu_{h0}, \Sigma_{h0})$. The prior distribution's parameters are $\mu_{\beta 0}, \Sigma_{\beta 0}$; $\mu_{\alpha 0}, \Sigma_{\alpha 0}$; μ_{h0}, Σ_{h0} respectively.

For the non-linear parameter state space formed by models, MLE estimator requires repeated filtering to simultaneously estimate the numerous parameters in the state space, which can lead to over-parameterization and affect the accuracy of the estimation results(Bostanci & Yilmaz, 2020). Nin this paper, we propose a MCMC estimation method based on Bayesian inference. Under the prior probability distributions, we regard the time-varying parameters as latent variables and generate the posterior distribution. Use the newest information to update the parameter distribution at time t.

Given dataset $y = y_t^n$ and $\omega = \left(\Sigma_\beta, \Sigma_\alpha, \Sigma_h\right)$. We set prior probability density as $\pi(\omega)$ and generate sample from the conditional distribution: $\beta|\alpha, h, \sum_\beta, y$; $\sum_\beta|\beta$; $\alpha|\beta, h, \sum_\alpha, y$; $\sum_\alpha|\alpha$; $h|\beta, \alpha, \sum_h, y$; $\sum_h|h$ using the MCMC algorism. Where $h|\beta, h, \sum_h, y$ is the Stochastic volatility. $\beta\big|\alpha, \mathrm{h}, \sum_\beta, \mathrm{y}; \alpha\big|\beta, \mathrm{h}, \sum_\alpha, \mathrm{y}$ is generated from normal distribution and $\sum_\beta|\beta,\ \sum_\alpha|\alpha, \sum_h|h$ is generated from the inverse Gamma distribution under the conjugate prior.

For the construction of the dynamic network, we refer to the method in (Grant & Yung, 2021), selecting the time-varying parameter vector β as the adjacency matrix to construct a directed, weighted network that captures the sectoral co-movement of index return. This network measures the extent to which changes in variables are influenced by either their own past behavior or the behavior of other variables in the system under external shocks. The directionality of the network edges is determined by the sign of the estimated coefficients, while the weights are determined by the magnitude of these coefficients. The matrix element $\beta_{ij,t}$ reflects the direction and strength of the co-movement between industry i and industry j. A positive value indicates risk resonance, while a negative value suggests risk diversification. The larger absolute value of $\beta_{ij,t}$, the greater the influence of changes in industry i on the changes in industry j, and the higher the degree of co-movement between the two industries. To measure the impact of a particular industry on the overall network's cascade effect, we compute the equal-weighted average of the estimated coefficients for industry i at time t, denoted $\beta_{i,t}$, which serves as a proxy for the industry's influence on the entire network's co-movement at time t.

And in order to further explore the risk contagion mechanisms within financial complex networks, we follow the methods of (Geraci & Gnabo, 2018; C. Huang et al., 2020; Kosmidou et al., 2017; S. Wen et al., 2023; Yang et al., 2020) to dynamically estimate the sectoral network's topological structure. For each time cross-section, we calculate key network metrics, including *Closeness Centrality*, *Betweenness Centrality*, *Eigenvector Centrality*, *In-Degree Centrality*, and *Out-Degree Centrality* as indicators of the dynamic complex network. These metrics serve as moderating variables to examine the impact of both direct and indirect connections within the network on systemic risk contagion. The calculation methods are shown as follows:

Table 1: Network topological structure indicators

Name	Indicators	Calculation	Definition
Closeness Centrality	CC	$CC_j = \frac{N-1}{\sum_{j \neq i} d_{ji}}$	N is the total number of nodes. d_{ji} denotes the shortest distance from node j to node i. Closeness centrality measures the speed of risk contagion to other nodes. The larger the value of a node means the more important and riskier in the network.
Eigenvector Centrality	EC	$EC_j = \frac{1}{\nu} \sum_{k=1}^{N} a_{ij} EC_k$	ν is the maximum eigenvalue of the matrix; a_{ij} is an indicator function that yields 1 if there is an edge drawn from i to j, and 0 otherwise. We consider that connecting to a node with a high score results in a larger contribution than connecting to a node with a low score. In the risk transmission network, thus an institution can be seen as a key institution when it affects institutions with more connected edges.
Betweenness Centrality	BC	$BC_j = \frac{1}{(N-2)(N-1)} \sum_{\substack{k,l \\ j \neq k \neq l}} \frac{N_{kl}(j)}{N_{kl}}$	N_{kl} denotes the minimum number of distances from node k to node l; $N_{kl}(j)$ denotes the minimum number of distances through node j. An institution with greater Betweenness Centrality means that he has a greater ability to transmit risk from one institution to another.
Indegree Centrality	IDC	$IDC_{i,\ t} = \frac{1}{(N_t - 1)} \sum_{j \neq i} (j \rightarrow_t i)$	IDC measures the average intensity of the risk spillover taken on by financial institution i. N is the total number of nodes. It is a measure of vulnerability to financial spillovers.
Outdegree Centrality	ODC	$ODC_{i,\ t} = \frac{1}{(N_t - 1)} \sum_{j \neq i} (i \rightarrow_t j)$	ODC measures the standard of risk spillovers originating from institution i. Thus, financial institutions with high ODC are considered to severely affect other financial institutions associated with them.

3.2 Measurement of risk contagion

As the dependent variable, we use DCC-GARCH-Network-ΔCoVaR as the measurement of systemic risk contagion within the network(Adrian & Brunnermeier, 2016) (Chen et al., 2022; Jia et al., 2022). Let VaR_q^i is the extreme loss of index i at quantile q, X^i denotes the industry index return:

$$Prob\left(X^i \le VaR_q^i\right) = q \tag{8}$$

$$Prob\left(X^j \le CoVaR_q^{j|i} \middle| X^i = VaR_q^i\right) = q \tag{9}$$

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|i} - VaR_q^j \tag{10}$$

$CoVaR_q^{j|i}$ is the possible loss of industry j at quantile q conditional on industry i and $\Delta CoVaR_q^{j|i}$indicate the risk contagion from i to j.

We extend ΔCoVaR across the time dimension t to capture time-varying risk contagion. Additionally, we use a DCC-GARCH model to capture the nonlinear correlations and volatility clustering among the series. In Eq (11) r_t represents the asset price return series, and a_t denotes the white noise series.

$$r_t = \mu_t + \varepsilon_t \tag{11}$$

$$\varepsilon_t = \sigma_t a_t \tag{12}$$

$$r_t = \phi_0 + \phi_1 r_{t-1} + \varphi_1 \varepsilon_{t-1} \tag{13}$$

$$\sigma_i^2 = \beta_0 + \beta_1 r_{t-1}^2 + \beta_2 \sigma_{t-1}^2 \tag{14}$$

We use an ARMA-GARCH (1,1) process to model the above process. The conditional standard deviation σ_t is decomposed to calculate the time-varying correlation coefficient between series i and j:

$$\sigma_t = D_t R_t D_t \tag{15}$$

$$D_t = diag\left(\sqrt{h_t^i}, \sqrt{h_t^j}\right) \tag{16}$$

Where R_t represents the dynamic correlation coefficients, and D_t is the dynamic standard deviation matrix, constructed from the conditional standard deviations $\sqrt{h_t}$. The returns are standardized by the volatility σ as: $\epsilon_{it} = r_{it}/\sigma_{it}$, $\epsilon_{mt} = r_{jt}/\sigma_{jt}$. And the dynamic correlation coefficient is calculated as follows:

$$Cor\begin{pmatrix}\epsilon_{it}\\ \epsilon_{jt}\end{pmatrix} = R_t = \begin{bmatrix}1 & \rho_t\\ \rho_t & 1\end{bmatrix} = \mathrm{diag}(Q_{it})^{-\frac{1}{2}} Q_{it} \mathrm{diag}(Q_{it})^{-\frac{1}{2}} \tag{17}$$

$Q_{i,t}$ is the dynamic covariance matrix:

$$Q_{it} = (1-\alpha-\beta)S_i + \alpha \begin{bmatrix}\epsilon_{it-1}\\ \epsilon_{mt-1}\end{bmatrix}\begin{bmatrix}\epsilon_{it-1}\\ \epsilon_{mt-1}\end{bmatrix}' + \beta Q_{it-1} \tag{18}$$

Through Eq (18) we can estimate the parameter α and β and furtherly get DCC-GARCH-CoVaR as follows:

$$VaR_{q,t}^{i} = \widehat{\mu_t} - D(q)\widehat{h_t^i} \tag{19}$$

$$CoVaR_{q,t}^{j|i} = \gamma_t^{ij} VaR_{q,t}^{i} \tag{20}$$

$$\Delta CoVaR_{q,t}^{j|i} = \gamma_t^{ij}\left(VaR_{q,t}^{i} - VaR_{50,t}^{i}\right) \tag{21}$$

$$\gamma_t^{ij} = \rho_t^{ij}\frac{h_t^j}{h_t^i} \tag{22}$$

D(q) in Eq (19) is the distribution function of return I at significant level 1-q, $\widehat{\mu_t}$ and $\widehat{h_t}^2$ is the estimated expectation and variance of r_t^i. ρ_t^{ij} is the dynamic correlation coefficient.

For industries $i, j \in (1,2,3 \dots n)(i \neq j)$, we calculate the pairwise $\Delta CoVaR_{q,t}^{(j|i)}$ as the elements of risk contagion matrix in row i and column j. To measure the overall risk contagion level within the network, we use the equally weighted average of $\Delta CoVaR_{q,t}^{(j|i)}$ between industries as an aggregate measure. This approach captures the average systemic risk contagion across all industry pairs, providing a holistic view of contagion within the network.

$$\Delta\, CoVaR_{i,t} = \frac{1}{n}\sum_{j=1, j\neq i}^{n} \Delta CoVaR_{q,t}^{(j|i)} \tag{23}$$

3.3 Regression Model of Risk Contagion Mechanism

To explore the impact of the dynamic evolution of sectoral linkages (SL) on the risk contagion mechanism within the financial network, we design the baseline regression model as follows:

$$\Delta CoVaR_{i,t} = \beta_0 + \beta_1 SL_{i,t} + \sum_{k}^{n} \beta_k Control_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{24}$$

In the regression model, **Control** represents the set of control variables, and β_0 represents the impact of industry index co-movement on risk contagion within the complex network. $\beta_0 > 0$ indicates that higher sector linkages promote an increase in systemic risk contagion and otherwise means a diversification effect, which reducing the overall risk contagion within the network.

To further discuss the mechanism through which different network structures influence the relationship between network interconnectedness and risk contagion, we use the node characteristic indicators from **Table 2** as proxy variables for changes in network structure. The interaction terms with centralization adjustments **EC** × SL, **CC** × SL, **BC** × SL, **IDC** × SL, and **ODC** × SL are incorporated to construct the moderation effect model for the mechanism test, as shown in **Equation (25)**.

$$\Delta \mathrm{CoVaR}_{i,t} = \beta_0 + \beta_1 SL_{i,t} + \beta_2 Cen_{i,t} + \beta_3 SL_{i,t} \times Cen_{i,t} + \sum_{k}^{n} \beta_k Control_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{25}$$

In this model, $\mathrm{Cen}_{\mathrm{it}}$ represents the network characteristic variables, which correspond to various centrality measures of the nodes, including **Eigenvector Centrality (EC)**, **Closeness Centrality (CC)**, **In-Degree Centrality (IDC)**, and **Out-Degree Centrality (ODC)**. These measures capture different aspects of a node's position and its role in the network's risk transmission dynamics: **CC (Closeness Centrality)** and **EC (Eigenvector Centrality)** are used to measure the indirect risk transmission and amplification potential of a node. And **IDC (In-Degree Centrality)** and **ODC (Out-Degree Centrality)** measure the node's direct risk absorption (IDC) and risk output (ODC) capabilities. These indicators are particularly relevant in understanding the flow of risk between industries through direct connections. The interaction term **SL × Cen** reflects the moderating effect of the network's structural features on the relationship between sector linkage (**SL**) and risk transmission. Specifically, it shows how different network structural characteristics influence the process through which sector linkage affect the contagion of systemic ris*k.*

IV. Empirical Result

4.1 Sample description

We select daily trading data of Wind's primary industry indices return from January 2014 to March 2024 from Wind Database to construct the time-varying network. Regarding control variables, we consider both micro and macro variables that may influence the risk contagion. For the industrial micro level variable, we select industry market value (Size), profitability (ROE), average leverage ratio (Leverage), average turnover (Turnover), and liquidity condition (ILL)(Amihud, 2002). Existing research suggests that larger industries, due to the "too big to fail", are more likely to be sources of risk contagion. At the same time, industries with better profitability, liquidity, and lower debt ratios tend to have more stable intrinsic values and lower risk levels. The sample includes 5,353 listed companies across 11 A-share industries. Industry turnover data is directly sourced from the Wind database. For the other micro level variables, are calculated from the relevant indicators of listed companies in each industry, weighted by market value. As for macro level variables, we select market default risk and interest rate risk as proxies for macroeconomic conditions and market uncertainty, and uses the S&P 500 index return as a proxy for global market trends, to assess the impact of global economic fluctuations on the domestic market's systemic risk (Adrian & Brunnermeier, 2016). The financial data for the relevant listed companies are sourced from the CSMAR database.

All variables are explained in detail in Table 2. Given that financial data is reported quarterly, variables calculated from financial indicators are forward-filled to a monthly frequency. The original daily frequency of other variables is retained. To eliminate short-term noise in the daily frequency data and to adjust for the differences in data frequencies, daily data is resampled to monthly data using an equally weighted averaging method. Since the TVP-VAR model's estimated coefficients exhibit low noise and stable variation, monthly equal-weight averaging is an effective way to reflect the average connectedness degree of network nodes within the month. CoVaR and macro interest rate variables are based on the study of Adrian & Brunnermeier (2016), and using the monthly equally weighted average method ensures a reasonable representation of data characteristics. Regarding the handling of macroeconomic control variables, we follow the method of (H.-C. Huang et al., 2022), calculate the interaction term between the macro control variable X_t at time t. This method supplements control variables while addressing measurement errors in the core explanatory variable due to the omission of macro external factors. Detailed definitions are provided in Table 2.

4.2 Time-varying risk contagion and sector linkages

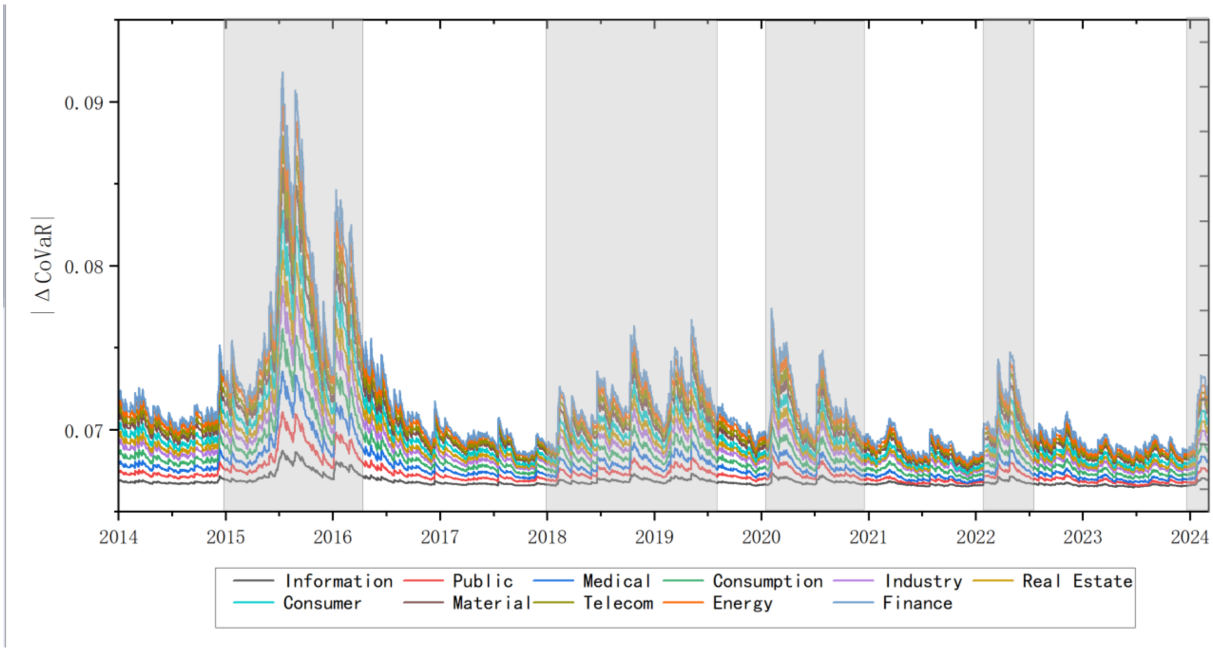

Figure 1: Time-varying network risk contagion

Figure 1 illustrates the DCC-GARCH-network CoVaR from January 2014 to March 2024 in the Chinese A-share market, representing the degree of risk contagion between industries. The vertical axis shows the risk contagion levels across different industries, with different colored curves representing each sector's risk contagion in the market. As indicated by the shaded regions, four distinct periods of significant risk contagion spikes are observed in the sample period: the "stock market crash" of 2015, the China-US trade war in 2018-2019, the COVID-19 in 2020, and the Russia-Ukraine conflict in early 2022. Different industry sectors exhibit both internal regularities and clear heterogeneity in their risk contagion characteristics. For instance, the finance, energy, consumer, and real estate sectors show similarly high levels of risk contagion, while healthcare and utilities sectors experience relatively low levels of risk contagion in the market. It is also noteworthy that during the five market shock events in the sample period, the risk contagion levels within the system tend to rise first, then return to a stable level. However, shocks occurring before 2020 generally exhibited a longer-lasting impact and higher risk contagion levels compared to those after 2020.

Table 2: variable definitions

Name	Variable	Definition
Dependent variable	$Network - \Delta CoVaR$ $(\Delta CoVaR)$	The measurement of risk contagion in the dynamic network. A greater value means a higher degree of systemic risk contagion.
Independent variable	*Sectoral Linkages*	The measurement of sector linages, positive value indicates co-movement in same direction and negative value presents a reverse

	(SL)	change.
Moderator variable	*CC*	Closeness centrality measures the speed of risk transmission and is used to measure the ability to transmit risk; the higher the value, the greater the ability to transmit risk
	EC	EC is used to measure influence. In a risk transmission network, the higher the value, the greater the risk transmission capacity.
	BC	BC represents the ability to transmit information; the higher the value, the greater the ability to transmit risk.
	IDC	IDC measures the strength of the direct risk spillover received by the node. The larger the value, the stronger the risk absorbing effect.
	ODC	ODC measures the intensity of direct risk spillover from a node. The larger the value, the stronger the direct risk contagion effect.
Control variable	*Lnmv*	The natural logarithm of the total market value of all firms in the sector
	ROE	The value weighted ROE of all firms in the sector
	Leverage	The value weighted leverage ratio of all firms in the sector
	Turnover	Sector index trading turnover ratio
	ILL	The value weighted ILL of all firms in the sector
	Default Risk	Changes in yield-to-maturity spreads between 10-year Treasury bonds and 10-year AAA-rated corporate bonds
	Interest Risk	Changes in YTM on three-month Treasury bonds
	S&P500	Monthly S&P500 Index Return

We use the average coefficient estimates to measure the average level of sector linkage. Figure 2 illustrates the dynamic linkage range of the Wind first-level industry indices in the Chinese stock market during the four shock periods. Each adjacency matrix in the figure represents the sector linkages at time t in the cross-section. For each shock event, we select the three time points corresponding to the start of the shaded interval in Figure 1, the peak of risk contagion, and the recovery of risk, and display their corresponding adjacency matrices. During different shock periods and phases of the same shock, the degree of inter-industry cascading clearly exhibits time-varying characteristics. For example, during the COVID-19 crisis, industries showed a stronger average mutual linkage, with the number and strength of sector linkages surpassing those observed in other shock periods. During the 2018 CN-US. trade conflict and the 2022 Russia-Ukraine conflict, the number of highly correlated industries was noticeably lower than during the 2020 shock, with the degree of sector linkages also slightly reduced. In contrast, during the 2015 stock market crash, sector linkages were generally at their lowest, though the financial industry exhibited a strong positive correlation with other industries, showing consistent behavior across sectors. Moreover, when comparing different cross-sections during shock periods, the sector linkages underwent a process of strengthening and then weakening. Initially, the aggregation of sector linkages significantly increased, but as the shock approached its end, these linkages gradually decreased. For example, we found that by the time of the public health crisis in 2019, sector linkages had already stabilized at a moderate level. In the COVID-19 crisis, sector linkages surged, only to gradually decline by the end of 2021.

Furthermore, the average interconnectedness within the network has shown a trend of gradual increase. The more pronounced sectoral linkages may becoming increasingly sensitive to risk outbreaks (Bardoscia et al., 2021; Grant & Yung, 2021). This on one hand, can enhance portfolio diversification, absorbing market-specific risks; however, it may also lead to greater market sensitivity to shocks. When the system experiences external shocks, this increased linkages could result in an amplified downturn across sectors, making it easier for systemic risks to be magnified. We will further examine this conclusion through a mechanism test.

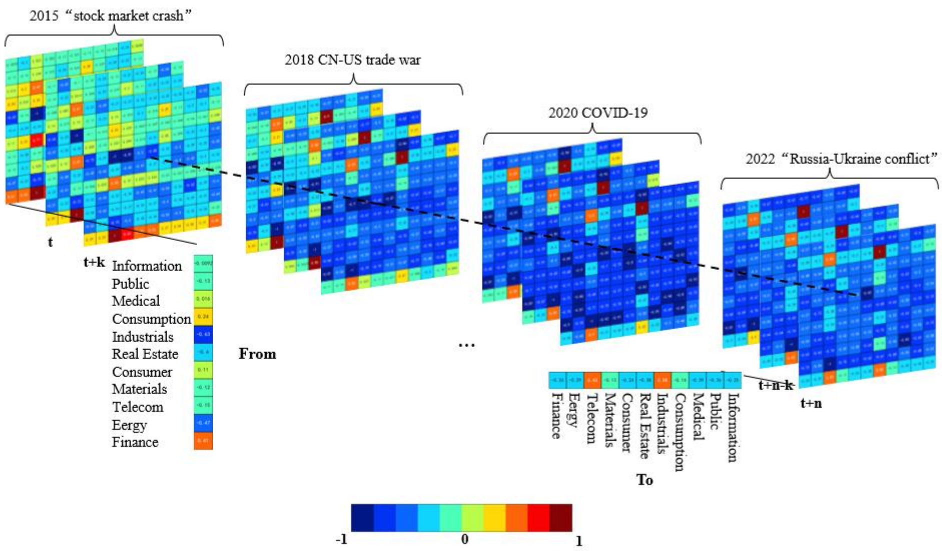

Figure 2: dynamic sector linkages at four shock events

4.3 Base line regression result

According to Eq (24), we use the industry sector linkages coefficient in continuous time as a proxy for industrial interconnectedness, and explore its relationship with risk contagion in the network, as shown in Table 3.

Columns (1) and (4) present the results after controlling for time and industry fixed effects. The sector linkage coefficients are 0.124 and 0.127, respectively, both significant at the 1% level. Columns (2), (3), (5), and (6) discuss the impact of lagged one-period and two-period cascades on systemic risk contagion. It is evident that the linkages between industries exhibit a robust predictive power for the intensification of systemic risk contagion. Moreover, as the lag order decreases, the predictive power strengthens. Therefore, Hypothesis 1a holds, suggesting that sectoral interconnectedness promotes risk contagion.

As for the control variables, industry market value is significantly positively correlated with risk contagion. Larger industries tend to have more interaction with counterparty, which in turn foster higher levels of risk contagion in the market. Additionally, we find that ROE, industry leverage, and turnover are significantly negatively correlated with risk contagion. That is, higher profitability and lower leverage help maintain the stability of an industry's asset value, thereby reducing risk contagion. And more active market trading also absorbs risks, acting to reduce risk. Regarding the macro control variables, the empirical results show that systemic default risk and interest rate risk are positively correlated with risk contagion. However, since the dependent variable in this study is based on industry index returns, the stock market, as a barometer of the macroeconomy, responds promptly to changes in the current macroeconomic environment. The time-varying risk contagion measurement already incorporates the latest information from industry index returns, and thus the macro explanatory variables in the model have no significant predictive power over the dependent variable, after correcting for certain measurement errors. Similarly, the correlation between the trends of overseas markets and risk contagion within the Chinese market is weaker, indicating that the state of the network within the Chinese market is more sensitive to changes in its internal structure than to external environmental factors.

Table 1: Baseline regression

	$\Delta\,CoVaR$					
	(1)	(2)	(3)	(4)	(5)	(6)
SL	0.124***			0.127***		
	(5.83)			(5.83)		
SL. Lag1		0.121***			0.124***	
		(5.66)			(5.65)	
SL. Lag2			0.118***			0.120***
			(5.47)			(5.45)
Size				0.061*	0.061*	0.060*
				(1.84)	(1.82)	(1.80)
ILL				300.264	289.227	281.759
				(0.14)	(0.13)	(0.13)
ROE				-0.511**	-0.512**	-0.513**
				(-2.26)	(-2.25)	(-2.25)

lev				-0.560**	-0.561**	-0.563**
				(-2.35)	(-2.34)	(-2.33)
turnover				-0.048**	-0.049**	-0.049**
				(-3.05)	(-3.05)	(-3.06)
Default Risk				0.164	0.090	0.286
				(0.13)	(0.07)	(0.22)
Interest Risk				0.322	0.193	0.118
				(0.51)	(0.28)	(0.17)
S&P 500				0.004	-0.007	-0.000
				(0.02)	(-0.03)	(-0.00)
_cons	0.988***	0.990***	0.993***	-0.385	-0.372	-0.364
	(45.63)	(45.35)	(45.10)	(-0.40)	(-0.38)	(-0.37)
Industry	YES	YES	YES	YES	YES	YES
Month	YES	YES	YES	YES	YES	YES
N	1353	1342	1331	1347	1336	1325
adj-R^2	0.845	0.844	0.844	0.847	0.847	0.846

4.4 Mechanism analysis

We further discuss the mechanism by which industry interconnectedness promotes risk contagion. Using the time-varying network topology characteristics of industry nodes as moderating variables, Figure 3 presents the time-varying results of four indicators: *Closeness Centrality* (CC), *Eigenvector Centrality* (EC), *Betweenness Centrality* (BC), *In-Degree Centrality* (IDC), and *Out-Degree Centrality* (ODC).

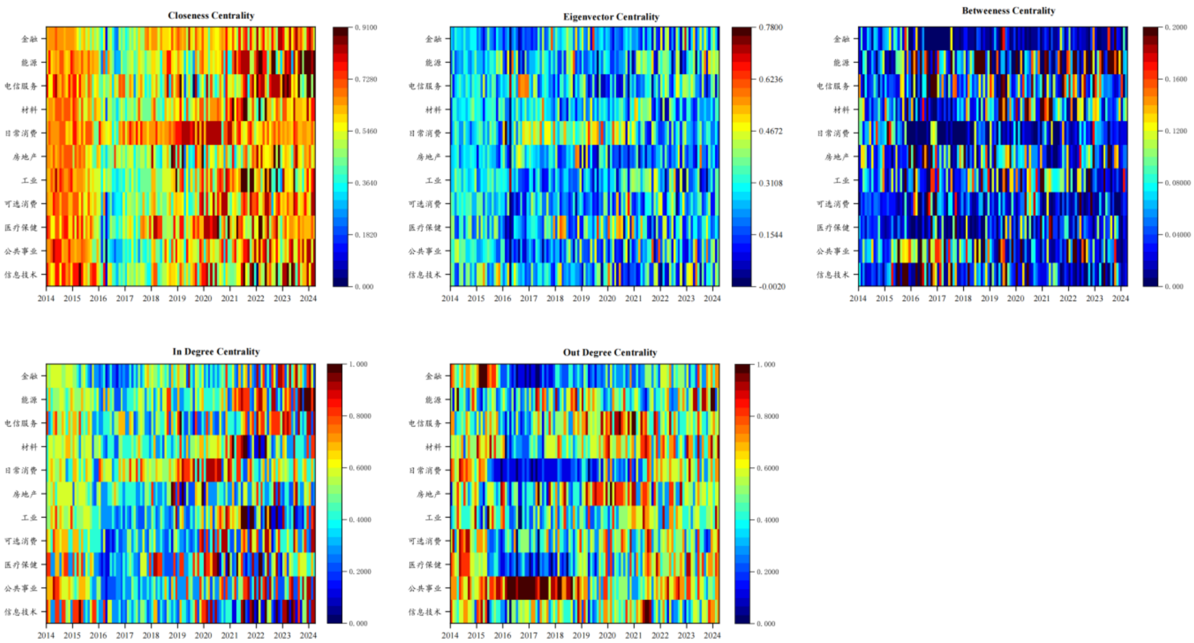

Figure 3：time-varying topological structure indicators

As shown in Figure 3, unlike network interconnectedness and risk contagion, the topological structure indicators don’t exhibit a distinct time-varying distribution pattern. These structural characteristics collectively reflect the role shifts of each node in the risk contagion process as well as the direction of contagion. Based on the empirical results in Table 3, increased industry interconnectedness positively promotes risk contagion. The network topology characteristics play varying moderating roles in this impact, leading to markedly different states of risk contagion (Gofman, 2017). In a network where direct linkages are dominant, nodes tend to have similar risk exposures. When an external shock occurs, contagion is driven primarily by direct interactions between nodes. This topology allows the shock to spread rapidly through nodes, and due to the lack of absorbing nodes, multiple nodes exhibit consistent risk outputs, causing cascades to intensify quickly within the network. Consequently, contagion occurs over a short period and affects a wide range. Conversely, in a network dominated by indirect linkages, nodes exhibit certain absorptive characteristics (Grant & Yung, 2021). After a shock, the risk transmission is multi-directional, and the risk contagion is moderated by various pathways across nodes. This structure requires the shock to pass through multiple in- and out-connections, making it difficult for contagion to spread quickly across the entire network. As a result, risk contagion grows gradually, displaying a slower propagation pattern.

Table 4 presents the regression results of the moderating effects of network connectivity and node structural characteristics. The results in Columns (1) - (3) show that the interaction terms of industry connectivity with eigenvector centrality, closeness centrality, and betweenness centrality are not significant, indicating that indirect connections between industries do not impact the positive effect of cascading on risk contagion. In Columns (4) and (5), only the out-degree centrality indicator shows a significant positive correlation with risk contagion, suggesting that risk contagion across Chinese industries is characterized by a rapid surge mechanism driven by direct connections. In highly connected industries, price changes directly impact the market. When external shocks occur, the linkages between industries intensify, as there is no indirect risk transmission or risk absorption in the contagion process. Industries with higher out-degree centrality quickly transmit their systemic risk to the broader market, resulting in a sharp surge in contagion levels during shock periods, consistent with the rapid increase in ΔCoVaR in the gray-shaded regions of Figure 1. This supports Hypothesis 2a for the Chinese industry sector network, as this structural characteristic prevents the market from having sufficient buffer time and risk absorption mechanisms during shocks, causing the risk to rapidly spillover from the originating node to other industries.

Regulatory authorities should closely monitor the time-varying characteristics of nodes' out-degree centrality, implementing policies to swiftly cap surges in the out-degree centrality of centralized nodes, preventing these nodes from cascading risk to other industries. Additionally, in networks characterized by stronger direct connections, early warning mechanisms should be emphasized, incorporating the interconnectedness indicators into the real-time monitoring framework. Due to this structural feature, risk contagion between industries can quickly accelerate during shock events, amplifying homogeneity among industries and causing synchronous declines within the market.

Table 4：Mechanism test

	$\Delta\, CoVaR$				
	(1)	(2)	(3)	(4)	(5)
SL	0.125***	0.124***	0.129***	0.124***	0.132***
	(5.76)	(5.66)	(5.95)	(5.68)	(6.12)
EC	-0.011				
	(-0.14)				
EC x SL	-0.094				
	(-1.40)				
CC		-0.112			
		(-1.23)			
CC x SL		-0.069			
		(-1.20)			
BC			-0.187		
			(-1.17)		
BC x SL			0.203		
			(1.57)		
IDC				-0.032	
				(-0.61)	
IDC x SL				-0.055	
				(-1.35)	
ODC					0.124**
					(2.31)
ODC x SL					0.150***
					(4.25)
_cons	-0.353	-0.317	-0.357	-0.333	-0.305
	(-0.37)	(-0.33)	(-0.37)	(-0.34)	(-0.32)
Controls	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES
Month	YES	YES	YES	YES	YES
N	1347	1347	1347	1347	1347
$adj.R^2$	0.847	0.847	0.848	0.847	0.850

4.5. Endogenous treatment

4.5.1. Instrumental variables

Existing literatures have found that risk contagion within the market is not a unidirectional process. The co-movement of asset prices increases cross-industry connectedness, with this high connectivity between industries forming a contagion channel during crises, which constitutes the first phase of risk contagion (Billio et al., 2012). However, the elevated level of risk contagion can trigger widespread asset devaluation and collateral sell-offs within the market (Duarte & Eisnbach, 2021). This causes entities that were initially stable during the first phase of contagion to become entangled, leading to a larger-scale decline in asset prices and creating a “downward spiral” in market operations. Therefore, there is a reverse causality between risk contagion and sector linkages.

To overcome the endogeneity from reverse causality, this we construct an instrumental variable for sectoral linkages that satisfies both relevance and exogeneity requirements. In an efficient market, all institutions are expected to respond to market information promptly. However, empirical financial studies have observed a "lead-lag effect" in stock markets, where different companies react at varying speeds to the same fundamental information. Some companies can quickly respond to new information, while others exhibit delayed reactions. Geraci and Gnabo (2018) find that stocks from companies headquartered in the same geographic region are influenced by the same fundamental factors. The geographical connection accelerates the transmission of information, resulting in synchronized price movements for stocks within the same region. In this study, we use the province of the listed company's registration as a proxy for its geographic coordinates. The sample of listed companies is classified by industry, and the spatial distance between the registered locations of companies in two different industries is calculated. The average distance is used as the proxy indicator for the cross-industry spatial distance (*GeoDis*). We employ the γ_{ij}^{C} to assess the pairwise clustering degree between industry i and industry j, which serves as an indicator for the degree of geographical proximity (*GeoLocal*) between the two industries[1]. The higher the degree of co-location between industries, the stronger the spatial connectivity. Considering the differences in information transmission across time and space dimensions in financial markets, a shorter average spatial distance between two industries and a higher degree of spatial connectivity indicates faster information transmission. When a significant fluctuation occurs in one industry index, new

[1] The calculation of GeoLocal is shown in the appendix A

information will quickly affect other closely connected industries, leading to synchronized sector movements and an increase in industrial connectivity.

Using ***GeoDis*** and ***GeoLocal*** as instrumental variables, we perform a 2SLS estimation. Column (1) of Table 4 presents the estimation results for the first stage, showing that the spatial distance distribution and spatial clustering degree of industries' interconnectedness. Specifically, the higher the spatial clustering of industries and the shorter the average geographical distance between institutions within an industry, the higher the degree of connectivity. Column (2) reports the second-stage estimation results, with the primary coefficients remaining consistent with the baseline regression. The iv-regression result indicate that, even after accounting for reverse causality and removing endogeneity, the positive effect of interconnectedness on systemic risk contagion remains robust.

Table 4: Endogenous test

	IV		Natural experiment	
	SL	ΔCoVaR	ΔCoVaR	ΔCoVaR
	(1)	(2)	(3)	(4)
SL		0.841***		
		(5.49)		
DesSL × Covid			0.086**	0.102**
			(2.01)	(2.35)
GeoDis	-71.137***			
	(-6.62)			
GeoLocal	0.048***			
	(5.25)			
Controls	YES	YES	YES	YES
Industry	YES	YES	YES	YES
Month	YES	YES	YES	YES
N	1337	1337	1342	1337
Adj-R^2			0.841	0.844

4.5.2. Natural Experiment

This study also addresses potential endogeneity issues caused by omitted variables in the regression using a difference-in-differences (DID) approach. We apply COVID-19 as an exogenous shock, impacting the operations of various industries within the financial market to varying degrees and significantly increasing the correlations between asset prices within the financial market (Choi, 2023; So et al., 2021. As shown in Figure 2, after the onset of the global public health crisis in 2020, the sectoral interconnectedness in the dynamic network significantly increased. Based on the above analysis, this study designs a natural experiment by hypothesizing that, following the COVID-19 shock, the sectoral linkages within China's financial market become stronger. Resulting in an amplify of the risk contagion within the network, while the outbreak of the pandemic is an exogenous variable unrelated to the characteristics of the industries. Based on this we construct the following difference-in-differences (DID) model:

$$\Delta CoVaR_{i,t} = \beta_0 + \beta_1 (DesSL \times Coivd)_{i,t} + \sum_{k}^{n} \beta_k Control_{i,t} + \mu_i + \lambda_t + \varepsilon_{i,t} \tag{26}$$

In this model, *DesCon* is a dummy variable representing the connectivity status, defined based on the median value of the *Con* indicator across industries in the sample. Industries with a *Con* value above the sample median are assigned *DesCon = 1*, while those below are assigned *DesCon = 0*. *Covid* is a dummy variable for the COVID-19, set to 1 from January 2020 onward and 0 for prior periods, considering that the pandemic began in late 2019. Other variable symbols remain consistent with previous specifications. Columns (3) and (4) of Table 4 report the regression results. In Column (3), the interaction term coefficient β_1 indicates that, after the COVID-19 shock event, industries with high connectivity contributed 8% more to network risk contagion than they did before the event, a result significant at the 5% level. After controlling for the effects of other variables on risk contagion, sectors in a highly connected state exhibited 9.5%[2] greater risk contagion capacity compared to the pre-crisis period, and this result remains significant at the 5% level. The widespread impact of the pandemic affected numerous sectors, including finance, industrials, and consumer, disrupting existing supply-demand structures and operational models. To meet production and operational demands, companies began engaging in broader cross-industry collaborations, resulting in more extensive business linkages within the market. This heightened network connectivity acts as a conduit for risk contagion: under extreme market conditions, a substantial price drop in one industry index can rapidly propagate, amplifying information dissemination and the spread of panic. This creates a pronounced "herding effect," with investors withdrawing funds from other sectors simultaneously, leading to a cascading decline in asset prices across the market.

4.6 Heterogeneity analysis

[2] Mean value of $\Delta CoVaR$ is 1.098, so the coefficient economic effect is 0.086/1.098=0.078; 0.102/1.098=0.095.

We selected industry groupings that are significantly influenced by fundamental capital factors and are more likely to exhibit similar risk exposures: cyclical versus non-cyclical industries, financial versus non-financial industries, as well as crisis versus non-crisis periods during market downturns. These groupings are used to explore the characteristics of risk contagion within the network.

4.6.1. Cyclical industries

We employ the CSI 300 cyclical industry classification method, categorizing finance, energy, materials, industrials, and consumer sectors as cyclical industries, with all other sectors classified as non-cyclical. Regression analyses are then conducted by grouping these industries, and the results are presented in Table 6. In Column (1), the estimated coefficients for the core explanatory variable and the moderating effect of the interaction term are 0.167 and 0.218, respectively, with higher values and significance levels than the non-cyclical industry sample. We observe that the five cyclical industries—finance, energy, materials, industrials, and consumer are more prone to cross-industry linkages, thereby amplifying risk contagion within the network.

On one hand, cyclical industries are more dependent on sufficient fundamental capital; their large capital demands make these capital-intensive sectors reliant on the performance of various national economic sectors for sales and profitability. For instance, energy, materials, industrials, and consumer discretionary industries are naturally intertwined through supply chain connections, where the upstream production and sales revenues directly serve as raw materials and cost inputs for downstream industries. This inherent linkage forms a strong correlation. More importantly, with increasing financialization, cyclical industries increasingly rely on financial market instruments for fundraising, cost management, and even securing sales channels and profit margins. This not only deepens cross-period dependencies between industries but also significantly intensifies their interdependence on financial market fundamentals. Economic cycles are thus more prominently reflected in these sectors through the fundamentals of the financial market, which acts as a barometer for the economy. We posit that the intensified contagion observed in cyclical industries during crisis periods is rooted in their cross-period dependence on financial market fundamentals. This increased dependency creates similar risk exposures to financial fundamentals. When financial market volatility occurs, the impact of this risk is stronger on cyclical industries. For China's industry network, where direct linkages predominantly shape the network structure, cyclical industries are expected to spill over more risk during crises, as corroborated by our empirical results.

4.6.2. Finance Sector

Based on the analysis of industry cyclicality, we further explore the special role of the financial sector. In our study, the financial sector includes banks, securities firms, diversified financial institutions, and the real estate industry, given the significant amount of credit products and debt financing prevalent in the Chinese real estate sector. The results of the grouped regressions are presented in Tables (3) and (4). The significant promote effect from financial industry (0.181) is much larger than that of the non-financial industries (0.043) in terms of risk contagion within the network. Nodes with higher network out-degree characteristics play a dominant role (0.412), whereas the interaction term of the network out-degree and association in non-financial industries is not significant. The coefficients and significance levels for the financial sector are stronger than those for the non-financial group. We conducted a Fisher combination test to check the difference of two groups, and the results show that the differences are statistically significant at the 1% level. This indicates that the financial sector exhibits a higher capacity for risk linkage and plays a more significant role in risk contagion compared to the non-financial sector.

In China's industry network, where direct linkages dominate, there is a lack of risk diversification, which prevents the formation of effective risk absorption. The increasing interconnectedness on financial institutions deepens the connection between sectors and the financial industry in both temporal and magnitude. The resulting similarity in risk exposures amplifies the impact of shocks. In other words, due to the dominance of direct linkages formed by shocks, this intertemporal dependence places the financial sector at the center of the risk contagion network, making it a major driver of systemic risk contagion. During external market shocks, the financial sector becomes the key force that triggers a more significant market price downturn.

Table 2：Heterogeneity analysis

	$\Delta CoVaR$					
	cyclical	Non-cyclical	Finance	Non-finance	Shock period	Non-shock period
	(1)	(2)	(3)	(4)	(5)	(6)
SL	0.167***	0.083**	0.181*	0.043*	0.196***	0.052***
	(5.25)	(3.06)	(1.93)	(1.75)	(4.84)	(5.38)

ODC x SL	0.218***	-0.044	0.412***	0.019	0.185**	0.031*
	(5.82)	(-0.67)	(6.79)	(0.37)	(2.98)	(1.89)
_cons	-4.792**	3.460**	26.730*	1.150	-0.996	-0.616
	(-2.03)	(3.02)	(1.86)	(1.05)	(-0.47)	(-1.56)
Controls	YES	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES	YES
Month	YES	YES	YES	YES	YES	YES
N	605	732	234	1098	581	756
Adj-R^2	0.910	0.805	0.952	0.833	0.872	0.924
p-value SL	0.065		0.04		0.000	
p-value: ODC× SL	0.000		0.01		0.150	

4.6.3. Shock event period

Based on the special role of cyclical industries, particularly the financial sector, in direct-linkage-dominated networks, we further investigate whether the network structural characteristics during periods of shock and stability have an asymmetric effect on industry association and risk contagion. Referring to the five major market shocks between 2014 and 2024, as shown in Figure 1, we define the shaded areas as crisis periods, with the remaining periods classified as non-crisis periods. The results of the grouped regressions are presented in Columns (5) and (6) of Table 6. During crisis periods, the positive effect of network interconnectedness on risk contagion is significantly stronger than during non-crisis periods. During market downturns, the formation of strong linkages between industries promotes the contagion of risk within the network. In Columns (5) and (6), the network out-degree has a significant positive effect on risk contagion during the crisis period (0.196). In China's direct-linkage-dominated network structure, industries with higher out-degree centrality during crises will exert a stronger positive influence on risk contagion within the market.

Summarizing the above conclusions, we find that the cascade effects between industries in China positively promote risk contagion, and the direct linkages between nodes in the network accelerate the rapid escalation of systemic risk contagion. When the network faces an external shock, industries with similar risk exposures, particularly cyclical industries like finance, are more susceptible to risk shocks. Due to the lack of risk absorption structures within the network, the risk formed by nodes (industries) with higher out-degree centrality is amplified rapidly and spreads throughout the market. Therefore, it is crucial to monitor real-time changes in the linkages between sectors with higher out-degree centrality, particularly in cyclical industries, as the intertemporal dependence between industries and the financial sector deepens. Moreover, given the asymmetric characteristics of risk contagion in China's industry network, we must be vigilant about the cascading jumps of nodes with higher out-degree centrality in continuous time. Preventing these changes from rapidly spreading throughout the market is vital to mitigating systemic risk.

4.7 Robustness check

This study conducts robustness checks on the baseline regression results along three dimensions:

First, we substitute the explanatory variable and apply a moving-window VAR to recalculate the time-varying network adjacency matrix, which serves as a measure of network interconnectedness and sectoral co-movement between industries. After controlling for industry heterogeneity, the regression results remain consistent with the baseline, confirming that an increase in network cascade effects promotes risk contagion within the market. Second, we alter the estimation method for the dependent variable by using quantile regression to recalculate ΔCoVaR, representing the level of systemic risk contagion among industries. Using this as the dependent variable in the regression, we obtain similarly significant results. Finally, we introduce additional control variables. Building on the original model, we incorporate indicators that influence index performance and investor choices, such as price-to-earnings ratio (P/E), price-to-book ratio (P/B), and price-to-cash flow ratio (P/CF) for industry index trading. The conclusions remain robust even with these added control variables.

V. Conclusions

With the deepening of cross-industry cooperation and the increasing financialization of industries, there is an increasingly significant intertemporal dependence and complex relationship between industry sectors, especially with the financial sector. By constructing a dynamic network of sector linkages in the Chinese stock market, this paper investigates the relationship between sector linkages and the transmission of systemic financial risk, as well as the specific mechanisms. The research findings are as follows:

(i) Based on the TVP-VAR model, this paper constructs a continuous-time complex network of 11 Chinese industries from January 2014 to March 2024 using Wind's first-level industry indices. Through analysis of time-varying network connectedness and DCC-GARCH-network CoVaR results, we find that the degree of sector linkages displays significant time-varying characteristics during different shock periods and stages of the same shock. The level of risk contagion between industries shows four distinct surge periods within the sample range, and different industry sectors exhibit heterogeneous risk contagion behaviors.

(ii) The regression result shows that, sector linkages in the Chinese stock market positively promote the contagion of systemic risk. In China’s sectoral linkage network shows both: "too big to fail" and "too connected to fail." The profitability and leverage ratio of industries enhances the risk-bearing capacity of nodes, allowing them to resist external risk spillovers, thus preventing further risk accumulation. The level of market trading activity can absorb risk and reduce the risk contagion.

(iii) Further mechanism tests reveal that the risk contagion in China’s sectoral linkage network is primarily driven by direct linkages. After a shock, the risk spreads quickly across the network, and the lack of absorption nodes leads to consistent risk output across multiple nodes. This causes a short transmission time and a broad radiation range. sectors with higher out-degree centrality have stronger risk output to other nodes, leading to a rapid surge in risk contagion within the market during shock periods. In the heterogeneity analysis, we further confirm that, for China’s cyclical sectors, especially the financial sector, play a more significant role in promoting risk contagion. This effect is asymmetric, especially during market downturns. We argue that the amplifying effect of cyclical sectors arises from their intertemporal dependence on the fundamentals of the financial market. The deepening of this dependence leads to similar risk exposures to financial fundamentals. When these fundamentals experience shocks, similar risk exposures result in a stronger impact on cyclical industries. We address potential endogeneity in our research through instrumental variables and natural experiments, and conduct robustness checks from three dimensions to ensure the consistency of the results.

The network in China is characterized by a structure dominated by direct linkages. Regulatory authorities need to pay special attention to real-time changes in the sector linkages within the network and set up policy intervention plans in advance for nodes with rapidly increasing out-degree centrality, preventing such nodes from causing broader risk contagion. It is necessary to identify the core parts of the risk transmission network in real-time and implement differentiated regulation for industries and sectors more sensitive to changes in the market environment. At the same time, this type of network, with its direct link structure and the existence of consistent risk transmission directions, enables rapid risk contagion in the short term. Therefore, more attention should be given to the design of early warning mechanisms for risk transmission. Regulators should closely monitor the external shocks and incorporate continuous-time linkage indicators into the macro-prudential regulatory framework to prevent risk amplification caused by network structures, which may lead to interconnected declines. Regulatory authorities should further strengthen counter-cyclical supervision, ensuring sufficient capacity and smooth operation of the overall financial market, and resisting large-scale malicious continuous declines in asset prices and risk contagion during periods of market stress due to increased asset price correlations. Regulators should combine early prevention, differentiated regulation, and counter-cyclical management to mitigate systemic risks and ensure the stable operation of China’s financial markets.

Reference

Acharya, V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring Systemic Risk. *Review of Financial Studies, 30*(1), 2-47.

Adrian, T., & Brunnermeier, M. K. (2016). CoVaR. *Social Science Electronic Publishing, 106*(7), 1705-1741.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets, 5*(1), 31-56. doi:https://doi.org/10.1016/S1386-4181(01)00024-6

Amini, H., & Minca, A. (2016). Inhomogeneous Financial Networks and Contagious Links. *Operations Research, 64*(5), 1109-1120. doi:10.1287/opre.2016.1540

Bardoscia, M., Barucca, P., Battiston, S., Caccioli, F., Cimini, G., Garlaschelli, D., . . . Caldarelli, G. (2021). The physics of financial networks. *Nature Reviews Physics, 3*(7), 490-507. doi:10.1038/s42254-021-00322-5

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics, 104*(3), 535-559. doi:https://doi.org/10.1016/j.jfineco.2011.12.010

Bostanci, G., & Yilmaz, K. (2020). How connected is the global sovereign credit risk network? *Journal of Banking & Finance, 113*, 105761. doi:https://doi.org/10.1016/j.jbankfin.2020.105761

Brownlees, C., & Engle, R. F. (2016). SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. *Review of Financial Studies, 30*(1), 48-79.

Buraschi, A., & Tebaldi, C. (2023). Financial Contagion in Network Economies and Asset Prices. *Management Science, 70*(1), 484-506. doi:10.1287/mnsc.2023.4687

Chen, Y., Mo, D., & Xu, Z. (2022). A study of interconnections and contagion among Chinese financial institutions using a ΔCoVaR network. *Finance Research Letters, 45*, 102395. doi:https://doi.org/10.1016/j.frl.2021.102395

Choi, S.-Y. (2023). The dynamic network of industries in US stock market: Evidence of GFC, COVID-19 pandemic and Russia-Ukraine war. *Heliyon, 9*(9), e19726. doi:https://doi.org/10.1016/j.heliyon.2023.e19726

Duarte, F., & Eisnbach, T. M. (2021). Fire-Sale Spillovers and Systemic Risk. *The Journal of Finance, 76*(3), 1251-1294. doi:https://doi.org/10.1111/jofi.13010

Fan, X., Wang, Y., & Wang, D. (2021). Network connectedness and China's systemic financial risk contagion——An analysis based on big data. *Pacific-Basin Finance Journal, 68*, 101322. doi:https://doi.org/10.1016/j.pacfin.2020.101322

Geraci, M. V., & Gnabo, J.-Y. (2018). Measuring Interconnectedness between Financial Institutions with Bayesian Time-Varying Vector Autoregressions. *Journal of Financial and Quantitative Analysis, 53*(3), 1371-1390. doi:10.1017/S0022109018000108

Gofman, M. (2017). Efficiency and stability of a financial architecture with too-interconnected-to-fail institutions. *Journal of Financial Economics, 124*(1), 113-146. doi:https://doi.org/10.1016/j.jfineco.2016.12.009

Gong, X.-L., Liu, X.-H., Xiong, X., & Zhang, W. (2019). Financial systemic risk measurement based on causal network connectedness analysis. *International Review of Economics & Finance, 64*, 290-307. doi:https://doi.org/10.1016/j.iref.2019.07.004

Grant, E., & Yung, J. (2021). The double-edged sword of global integration: Robustness, fragility, and contagion in the international firm network. *Journal of Applied Econometrics, 36*(6),

760-783. doi:https://doi.org/10.1002/jae.2839
Haldane, A. G. (2009). Rethinking the financial network.
Huang, C., Zhao, X., Su, R., Yang, X., & Yang, X. (2020). Dynamic network topology and market performance: A case of the Chinese stock market. *International Journal of Finance & Economics*.
Huang, H.-C., Wang, X., & Xiong, X. (2022). When macro time series meets micro panel data: A clear and present danger. *Energy Economics, 114*, 106289. doi:https://doi.org/10.1016/j.eneco.2022.106289
Jia, X., Liao, W., & Zhang, C. (2022). Commodity financialization and funding liquidity in China. *The North American Journal of Economics Finance, 60*, 101674.
Kapinos, P., Kishor, N. K., & Ma, J. (2022). Dynamic comovement among banks, systemic risk, and the macroeconomy. *Journal of Banking & Finance, 138*, 105894. doi:https://doi.org/10.1016/j.jbankfin.2020.105894
Kitsak, M., Gallos, L. K., Havlin, S., Liljeros, F., Muchnik, L., Stanley, H. E., & Makse, H. A. (2010). Identification of influential spreaders in complex networks. *Nature Physics, 6*(11), 888-893. doi:10.1038/nphys1746
Klages-Mundt, A., & Minca, A. (2020). Cascading Losses in Reinsurance Networks. *Management Science, 66*(9), 4246-4268. doi:10.1287/mnsc.2019.3389
Kosmidou, K., Kousenidis, D., Ladas, A., & Negkakis, C. (2017). Determinants of risk in the banking sector during the European Financial Crisis. *Journal of Financial Stability, 33*, 85-296.
Li, Y., Chen, S., Goodell, J. W., Yue, D., & Liu, X. (2023). Sectoral spillovers and systemic risks: Evidence from China. *Finance Research Letters, 55*, 104018. doi:https://doi.org/10.1016/j.frl.2023.104018
Markose, S., Giansante, S., & Shaghaghi, A. R. (2012). 'Too interconnected to fail' financial network of US CDS market: Topological fragility and systemic risk. *Journal of Economic Behavior & Organization, 83*(3), 627-646. doi:https://doi.org/10.1016/j.jebo.2012.05.016
Nakajima, J. (2011). Time-Varying Parameter VAR Model with Stochastic Volatility: An Overview of Methodology and Empirical Applications. *Monetary and Economic Studies, 29*, 107-142.
Nakajima, J., Kasuya, M., & Watanabe, T. (2011). Bayesian analysis of time-varying parameter vector autoregressive model for the Japanese economy and monetary policy. *Journal of the Japanese and International Economies, 25*(3), 225-245. doi:10.1016/j.jjie.2011.07.004
Nivorozhkin, E., & Chondrogiannis, I. (2022). Shifting balances of systemic risk in the Chinese banking sector: Determinants and trends. *Journal of International Financial Markets, Institutions and Money, 76*, 101465. doi:https://doi.org/10.1016/j.intfin.2021.101465
Oh, D. H., & Patton, A. J. (2017). Modeling Dependence in High Dimensions With Factor Copulas. *Journal of Business & Economic Statistics, 35*(1), 139-154. doi:10.1080/07350015.2015.1062384
Paddrik, M., Rajan, S., & Young, H. P. (2020). Contagion in Derivatives Markets. *Management Science, 66*(8), 3603-3616. doi:10.1287/mnsc.2019.3354
Paltalidis, N., Gounopoulos, D., Kizys, R., & Koutelidakis, Y. (2015). Transmission channels of systemic risk and contagion in the European financial network. *Journal of Banking & Finance, 61*, S36-S52. doi:https://doi.org/10.1016/j.jbankfin.2015.03.021
Tanna, S., sui, P., & Zhou, D. (2019). Financial Contagion in a Core-Periphery Interbank Network.

European Journal of Finance*. doi:10.1080/1351847X.2019.1630460

Wan, J., Yin, L., & Wu, Y. (2024). Return and volatility connectedness across global ESG stock indexes: Evidence from the time-frequency domain analysis. *International Review of Economics & Finance, 89*, 397-428. doi:https://doi.org/10.1016/j.iref.2023.10.038

Wang, G.-J., Jiang, Z.-Q., Lin, M., Xie, C., & Stanley, H. E. (2018). Interconnectedness and systemic risk of China's financial institutions. *Emerging Markets Review, 35*, 1-18. doi:https://doi.org/10.1016/j.ememar.2017.12.001

Wang, G.-J., Xie, C., He, K., & Stanley, H. E. (2017). Extreme risk spillover network: application to financial institutions. *Quantitative Finance, 17*(9), 1417-1433. doi:10.1080/14697688.2016.1272762

Wang, G.-J., Yi, S., Xie, C., & Stanley, H. E. (2021). Multilayer information spillover networks: measuring interconnectedness of financial institutions. *Quantitative Finance, 21*(7), 1163-1185. doi:10.1080/14697688.2020.1831047

Wen, D., & Wang, Y. (2021). Volatility linkages between stock and commodity markets revisited: Industry perspective and portfolio implications. *Resources Policy, 74*, 102374. doi:https://doi.org/10.1016/j.resourpol.2021.102374

Wen, S., Li, J., Huang, C., & Zhu, X. (2023). Extreme risk spillovers among traditional financial and FinTech institutions: A complex network perspective. *The Quarterly Review of Economics and Finance, 88*, 190-202. doi:https://doi.org/10.1016/j.qref.2023.01.005

Xu, Q., Yan, H., & Zhao, T. (2022). Contagion effect of systemic risk among industry sectors in China’s stock market. *The North American Journal of Economics and Finance, 59*, 101576. doi:https://doi.org/10.1016/j.najef.2021.101576

Yang, X., Wen, S., Zhao, X., & Huang, C. (2020). Systemic importance of financial institutions: A complex network perspective. *Physica A: Statistical Mechanics and its Applications, 545*, 123448.

Zedda, S., & Cannas, G. (2020). Analysis of banks’ systemic risk contribution and contagion determinants through the leave-one-out approach. *Journal of Banking & Finance, 112*, 105160. doi:https://doi.org/10.1016/j.jbankfin.2017.06.008

Zhou, D.-h., & Liu, X.-x. (2023). Do world stock markets “jump” together? A measure of high-frequency volatility risk spillover networks. *Journal of International Financial Markets, Institutions and Money, 88*, 101843. doi:https://doi.org/10.1016/j.intfin.2023.101843

Appendix A: Stationarity test

Table A1: Stationarity test

	Count	Mean	Std	Min	Max	Skew	Kurt	ADF(t)	ADF(p)
Energy	2714	0.0001	0.0172	-0.1044	0.0810	-0.6850	4.8521	-14.6016	0.0000
Materials	2714	0.0002	0.0178	-0.1019	0.0935	-0.9292	5.7577	-11.1987	0.0000
Industrial	2714	0.0002	0.0172	-0.1029	0.0944	-0.9345	6.8966	-10.9147	0.0000
Consumption	2714	0.0003	0.0167	-0.1041	0.0943	-0.9457	6.6109	-11.0799	0.0000
Consumer	2714	0.0004	0.0164	-0.1021	0.0933	-0.6413	4.6614	-10.7809	0.0000
Medical	2714	0.0003	0.0174	-0.1033	0.0949	-0.5523	4.6854	-13.8439	0.0000
Finance	2714	0.0002	0.0153	-0.0994	0.0864	-0.2721	5.8438	-9.2069	0.0000
Information	2714	0.0005	0.0211	-0.1046	0.0945	-0.6366	3.7142	-10.9009	0.0000
Telecom	2714	0.0003	0.0203	-0.1058	0.0959	-0.2350	4.4127	-37.7351	0.0000
Public	2714	0.0003	0.0154	-0.1048	0.0945	-0.9474	10.0017	-11.2761	0.0000
Real estate	2714	0.0000	0.0184	-0.0995	0.0941	-0.4638	4.3912	-15.0955	0.0000

Appendix B: Regression results of mechanism test (one period lag)

Table B1: Mechanism test (one period lag)

	$\Delta\ CoVaR$				
	(1)	(2)	(3)	(4)	(5)
SL. L1	0.126***	0.124***	0.129***	0.124***	0.133***
	(5.74)	(5.65)	(5.89)	(5.67)	(6.16)
EC	0.009				
	(0.10)				
EC × SL. L1	-0.044				
	(-0.65)				
CC		-0.079			
		(-0.86)			
CC × SL. L1		-0.040			
		(-0.70)			
BC			-0.015		
			(-0.09)		
BC × SL. L1			0.251*		
			(1.93)		
IDC				-0.015	
				(-0.28)	
IDC × SL. L1				-0.035	
				(-0.87)	
ODC					0.204***
					(3.81)
ODC×SL. L1					0.164***
					(4.66)
_cons	0.074**	0.075**	0.073**	0.074**	0.067**
	(2.20)	(2.22)	(2.17)	(2.18)	(2.03)
Controls	YES	YES	YES	YES	YES
Industry	YES	YES	YES	YES	YES
Month	YES	YES	YES	YES	YES
N	1347	1347	1347	1347	1347
$adj-R^2$	0.847	0.847	0.847	0.847	0.851

Appendix C: Calculation for the Instrumental Variables and Robustness Tests

C1: Calculation for the Industry Concentration Degree in Spatial Distribution

$$\gamma_{ij}{}^{c}=\frac{\sum_{m=1}^{M}\left(s_{mi}-x_{m}\right)\left(s_{mj}-x_{m}\right)}{1-\sum_{m=1}^{M}x_{m}^{2}} \tag{C-1}$$

In Eq (C-1), the larger the value of γ_{ij}^{c}, the higher the degree of co-location between industry i and industry j. M represents the number of basic units under the study space, which, in this paper, refers to the total number of different provinces where the listed companies in the industry are registered. Taking province m as an example, s_{mi} denotes the ratio of the number of listed companies in industry i that are registered in province mmm to the total number of companies in industry i across the entire study space. x_m represents the ratio of the number of companies listed on the A-share market that are registered in province m to the total number of companies in the entire study space. If there are N industries in the study space, then $N(N-1)/2$ paired industries can be obtained, each with a corresponding pairing aggregation coefficient.

C2：ΔCoVaR Based on Quantile Regression

Based on VaR, we define $CoVaR_{q,t}^{i|j}$ as the systemic risk contribution of variable i conditional on the shock of j. $CoVaR_{q,t}^{i|j}$ is defined by the $q\%$ quantile of the conditional distribution.

$$Pr(R^{i}\leqslant CoVaR_{q,t}^{i|j}|R^{j}=VaR_{q,t}^{j})=q\% \tag{C-2}$$

Where R^i represents the return of the industry index. To estimate the time-varying $VaR_{q,t}^{i}$ and $CoVaR_{q,t}^{i|m}$, we adopt a quantile regression at level q on a set of variables R^i and R^m. Using the regression model: $VaR_{q,t}^{i}=a+bM_{t-1}$ and $CoVaR_{q,t}^{i|m}=c+dVaR_{q,t}^{i}+eM_{t-1}$ to get the estimating parameters. We use CoVaR to measure the systemic risk contribution from a single industry sector.

Let m represent the entire financial market, then $CoVaR_q^{m|C(x^i)}$ measure the value-at-risk conditional on a risk event $C(X^i)$ occurring in industry i. $CoVaR_q^{m|C(x^i)}$ can be defined as the conditional probability distribution:

$$Pr(X^m|C(X^i) \leqslant CoVaR_q^{m|C(X^i)}) = q\% \tag{C-3}$$

The risk spillover from industry i to market m can be expressed as $\Delta CoVaR_q^{m|i}$, which represents the change in the CoVaR of the financial system m when industry i is in a normal state ($X^i = VaR_{50}^i$) and in a crisis state ($X^i = VaR_q^i$).

$$\Delta CoVaR_q^{m|i} = CoVaR_q^{m|X^i=VaR_q^i} - CoVaR_q^{m|X^i=VaR_{50}^i} \tag{C-4}$$

Substituting $X^i = VaR_q^i$ into the equation, we can obtain the CoVaR of industry i, denoted as $CoVaR_q^i$:

$$CoVaR_q^i = VaR_q^{m|X^i=VaR_q^i} = \hat{\alpha}_q + \hat{\beta}_q VaR_q^i \tag{C-5}$$

The systemic risk contribution $\Delta CoVaR_q^i$ of industry I can be calculated as Eq (C-6):

$$\Delta CoVaR_q^i = CoVaR_q^i - CoVaR_q^{m|VaR_{50}^i} = \hat{\beta}(VaR_q^i - VaR_{50}^i) \tag{C-6}$$

In the above equation, VaR_q^i and VaR_{50}^i represent the $q\%$ quantile and the median of industry i's losses, respectively. That is, the loss levels during a crisis period and under normal conditions. We can get $\hat{\beta}_q^i$ by performing a quantile regression of the financial system's loss X_q^m on industry i's loss X^i at the q% quantile. Then, by calculating the $\Delta CoVaR_q^i$. The higher the value of $\Delta CoVaR_q^i$, the stronger the industry's contagion effect in the market, indicating a higher systemic risk contribution.

C3: Robustness test

Table C1: Robustness test

	$\Delta CoVaR$					
	(1)	(2)	(3)	(4)	(5)	(6)
TVVAR			0.438**	0.005		
			-2.32	-0.05		
Con	0.006*	0.005**			0.085**	0.118***
	-1.92	-1.98			-2.05	-5.5
Lnmv	0.015***	0.013**	-0.375***	0.03	-0.375***	0.076**
	-4.55	-3.06	(-9.12)	-0.91	(-9.11)	-2.31
ILL	812.138**	682.606**	793.092	130.084	804.06	516.005
	-2.63	-2.57	-0.2	-0.06	-0.2	-0.24
ROE	-0.012	-0.069**	-0.620*	-0.505**	-0.652*	-0.429*
	(-0.43)	(-2.47)	(-1.66)	(-2.20)	(-1.74)	(-1.92)
Lev	0.038	-0.023	-2.379***	-0.479**	-2.471***	-0.482**
	-1.09	(-0.77)	(-5.36)	(-1.99)	(-5.55)	(-2.05)
Turnover	-0.001	0.004**	0.254***	-0.054***	0.247***	-0.041**
	(-0.85)	-2.06	-11.42	(-3.35)	-10.61	(-2.62)
Defualt Risk	0.11	-0.011	1.611	0.42	1.552	0.164
	-0.69	(-0.07)	-0.78	-0.34	-0.76	-0.13
Interest Risk	-0.036	0.092	0.28	0.052	0.415	0.298
	(-0.45)	-1.17	-0.27	-0.08	-0.4	-0.48
SP	500	0.01	-0.017	-0.827**	0.057	-0.843**
	-0.44	(-0.73)	(-2.76)	-0.29	(-2.81)	(-0.08)
PE					0	-0.000**
					-1	(-3.11)
PB					0.008	-0.017***
					-1.35	(-5.23)
CTM					0	0
					-0.84	(-1.16)
_cons	-0.528***	-0.443***	12.730***	0.585	12.677***	-0.763
	(-5.69)	(-3.69)	-10.73	-0.6	-10.66	(-0.80)
Industry	YES	YES	YES	YES	YES	YES
Month	YES	NO	YES	NO	YES	NO
N	1347	1347	1347	1347	1347	1347
adj. R2	0.246	0.496	0.424	0.843	0.423	0.852