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Research Article

Network Effects and Characteristics of Cross-Industrial Tail Risk Spillover in China

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In recent years, the Chinese capital market has suffered several violent shocks, and the characteristics of systemic risk contagion across industries and markets have become increasingly important. It brings great potential danger to the stability of financial markets. Therefore, exploring the risk spillover among the real sectors has gradually attracted the attention of scholars. This paper examines the cross-industrial tail risk spillover network in the Chinese financial market. The characteristics and the dynamic contribution of each industry in the tail risk transmission chains are explored. We use the ΔCoES-ENGDFM-LVDN model based on monthly data from 2006 to 2020 to measure the tail risk of 28 industries in China and form a cross-industrial tail risk spillover network. The results show that different industries have different levels of spillover and importance in the network. Tail risk mainly spills over from the nonfinancial sector to the financial sector. The nonbank financial industry is the main recipient of tail risk spillover and is becoming progressively more important in the risk network. In addition, with the promotion of industrial structure, emerging industries such as communications, computers, and health care have begun to play more important roles in the tail risk spillover network in China. This paper not only enriches the research in the areas of tail risk spillover and systemic risk, but also has implications for regulators to maintain financial stability and prevent financial risks.

1. Introduction

One of the important tasks of China's financial stability goal is to control risk spillover between the nonfinancial sector and financial sector and prevent cross-industrial or cross-market risk contagion. When the business performance of companies is poor, its negative impact may spread rapidly through the industry connection to the whole market. The deterioration of market fundamentals will trigger the increasing linkage between financial market return and risk. The tail risk spillover among industries will also amplify economic volatility. The linkages among industries have significantly exacerbated risk spillover effects and increased the impact of the nonfinancial sector on the financial system, giving rise to new challenges for preventing systemic risks. The industry-level systemic risk indicators include systemic risk contribution and systemic risk exposure. The former refers to the impact of an individual industry under extreme circumstances (e.g., the industry suffers severe losses) on the economic system, while the latter refers to the impact of the economy under extreme circumstances (e.g., the economy falls into a severe recession) on an individual industry. We consider the former. At the same time, since economic and financial variables are usually characterized by "sharp peaks and thick tails," the measurement of systemic risk should focus on the tail risks of industries and economies in extreme situations.

Tail risk is used not only in characterizing the extreme risks, but also to reflect the accumulation of risk spillover levels in extreme cases. Therefore, what is each industry contributing to the systemic risk in the tail risk network? Does the financial sector play a crucial role in risk spillover? How do the intensity, transmission direction, and path of tail risk spillover among industries vary with business cycles? This paper aims to answer these questions.

In recent years, research on the risk spillover among industries in the real sector has gradually attracted academic attention. Networks constructed with the mean and variance tend to underestimate the risk contagion level by ignoring tail risks in extreme cases. The drawbacks of failing to measure the incremental change in risk spillovers from normal to extreme states violate the purpose of Adrian and Brunnermeier [1] on improving the risk spillover measure. In addition, most of the networks constructed by existing studies, either based on causality detection or based on variance decomposition, are information or volatility spillover networks instead of risk spillover networks [2–6]. In addition, most of the existing studies [7, 8] focus on measuring the intensity scale of risk spillover, that is, the level of network association. Scare attention is given to the direction and path of risk transmission and other association structures [9–11]. There are very few studies [12, 13] that consider both the level and structure of association and assess the contribution of risk in the tail risk network.

Academic research has agreed on the level of correlation in China's economic and financial system with obvious cyclical characteristics. The probability of risk spillover in specific industries increases significantly, and the intensity of spillover varies with cyclical characteristics, showing obvious asymmetry in different cycles. Most of the existing studies often ignore the difference in tail risk spillover between the risk accumulation and the release stage [14–16]. To overcome these drawbacks, this paper studies the level and structure of the tail risk spillover network among industries in China, as well as the systemic contribution characteristics of each industry in the risk transmission network. We also aim to identify the core industries in the risk network and make forward-looking suggestions for regulation. Moreover, we identify the differences in the above characteristics in the risk accumulation or release stages.

We introduce a periodic perspective to measure cross-industrial upside and downside tail risks and construct a tail risk spillover network with cyclical properties among China's industries using ΔCoES-ENGDFM-LVDN models, which may be more effective in measuring the cross-industrial tail risk spillover network effects. Specifically, we analyse the key industries in the contagion chain during tail risk spillover and examine the intensity, direction, path, and center of tail risk spillover according to the risk network. Then, from a dynamic perspective, we further consider the trend of tail risk spillover in each industry. We compare the spillover effects both in the risk accumulation stage and release stage and analyze the spillover levels from normal to extreme states. From the time dimension, we longitudinally examine the evolutionary relationship of tail risk spillover among industries in the full sample and each subsample, comparing the differences in spillover effects within different sample periods for the same risk phase (upside risk accumulation or downside risk mitigation).

First, we begin our test by constructing a risk network and analyzing cross-industrial risk spillover effects directly for tail risk. Compared to the networks constructed from the returns and variance [1, 17, 18], tail risk could reflect the incremental change in the level of risk spillover from normal to extreme states. It is possible to avoid the underestimation of the level of risk contagion caused by return and volatility [19, 20].

Second, we use ΔCoES instead of ΔCoVaR, which contains both left-tailed and right-tailed information and is based on a long-term stress scenario. However, ΔCoES does not measure network effects, resulting in tail risk spillover being underestimated [21]. The General Dynamic Factor Model (GDFM) proves the consistency of the estimators when both the sample and time series dimensions are infinite, but it is calculated only for the fluctuation spillover relation. Elastic Net (EN) combines the advantages of LASSO regression and ridge regression. Therefore, this paper introduces ΔCoES into the GDFM with EN to construct and estimate the tail risk spillover network with periodicity among China's industries, which can overcome the limitations of the abovementioned methods. It could also demonstrate the tail risk spillover across industries in the risk accumulation stage and release stage. The results indicate that there are an overall persistent nonlinear spillover effect and significant periodicity effect among industry tail risks in China. Cross-industrial tail risk spillover is more pronounced in the risk release stage. However, the total degree of spillover in the risk accumulation stage gradually grows and has exceeded the total degree in the release stage. This suggests that while the scope of cross-industrial tail risk spillover in China is gradually expanding, the downside risk has not been released sharply.

Third, this paper considers the level of industry tail risk association, structure, and network contribution for both the full sample and the dynamic evolution of each stage. We explore the pattern of risk spillover from normal to extreme and test the tail risk spillover in key industries. It forms a useful complement to previous studies on cross-industrial risk spillover.

This paper contributes to the following streams of literature:

First, identification and measurement of tail risk. Traditional methods are divided into three categories based on real operating business data, directly generated based on complex network theory, and based on financial market data such as stock prices. Linear or nonlinear Granger causality detection [22, 23], generalized variance decomposition [2], LASSO regression [21, 24], and TENET networks [25] were mainly used. In recent years, the construction of correlation networks based on financial market data has gained the attention and recognition of scholars. The network constructed through high-frequency financial market data is not limited to a particular form, which can overcome the untimely assessment of cross-industrial risk spillover caused by the lag of low-frequency data and measure the global and integrated channel effects formed by cross-industrial tail risk spillover [2, 26, 27]. Barigozzi and Hallin [28] use the EN approach to deal with the high-dimensional time series estimation problem involved in the GDFM model and further test the volatility spillover effect among industries in the SP100 index jointly with the LVDN, providing a reference for the study.

The second is the risk spillover characteristics among industries. Most of the existing studies focus on risk contagion within the financial sector, few papers analyze the tail risk diffusion relationship among nonfinancial sectors, and the empirical findings remain controversial [29, 30]. On the one hand, some studies focus on volatility spillover rather than tail risk spillover; on the other hand, the related literature focuses on tail risk to the downside and ignores the upside [31–33]. It neither captures the differences presented by tail risk spillover in the process of upside risk accumulation and downside risk mitigation nor the process of incremental changes in the level of risk spillover.

Finally, the impact of periodic factors on tail risk spillover is examined. The degree of risk spillover among China's financial institutions was at a relatively high level during the subprime mortgage crisis and the implementation of the new round of easing monetary policy in the United States. Some studies suggest that the level of systemic correlation of financial institutions in China has a distinctly periodic character. Some Chinese scholars measure the downside risks of 11 industries in China. The results clearly demonstrate that when the economic downwards pressure increases, facing greater policy uncertainty or implementing expansionary credit policies, there will be more significant risk contagion among industries. At the same time, the nonfinancial sector has strong explanatory power for systemic risk. However, the current research focusing on the impact of cyclical factors on tail risk spillover among industries in the nonfinancial sector still needs to be supplemented.

The rest of this paper is organized as follows: Section 2 presents the methodology, introduces the data, and gives the measurement results of relevant variables. Section 3 reports empirical results and further analysis. Section 4 provides recommendations for improving cross-industrial risk spillover regulation in China.

2. Methodology and Data

2.1. ΔCoES Method to Calculate Upside and Downside Tail Risk. Using ES as a risk metric and replacing conditional events with $X^i \leq VaR_p^i$, Adrian and Brunnermeier [1] present estimates for CoES that measure the tail effect of individual risk contribution. We improved on these and learned the method from Brownlees and Engle [34] to estimate CoES. As a result, we can capture not only the institutions' systemic risk exposure and the institutions' contribution to systemic risk at the same time, but also the long-term stress profiles. It can also use the risk-taking behavior and risk accumulation of institutions during the upside to predict risk mitigation in the downside, thus addressing the procyclicality of the contemporaneous risk metric. Empirical tests show that the upside ΔCoES (as in equation (1)) is appropriate as a forward-looking measure of tail risk, while the downside ΔCoES (as in equation (2)) can lead CoVaR and CoES.

This paper extends the application of the ΔCoES model, which is no longer limited to the financial sector. Using the overall industry-wide market as a benchmark, measure the upside and downside ΔCoES values of tail risk for each industry. The specific calculation steps are as follows: the BEKK-MGARCH model is used to estimate the variance equation of log returns for each industry. The distribution of future one-month returns is simulated by the residual bootstrap method, where the forecast period $h = 22$ denotes the actual number of trading days in a month, and S denotes the number of simulations. The larger the value of S is, the better the simulation effect is, so we take $S = 105$. Based on the information for period T and conditional on the arithmetic rate of return R for the next month ($h = 22$), the $\Delta\text{CoES}^{i|N}$ values for each industry are obtained separately.

$$\begin{aligned}\text{upside}\Delta\text{CoES}_T^{i|N} &= E_T\left(R_{i,T+1:\,T+h} | R_{N,T+1:\,T+h} \leq VaR_{95}^N\right)\\ &\quad - E_T\left(R_{i,T+1:\,T+h} | R_{N,T+1:\,T+h} \leq \text{VaR}_{50}^N\right),\end{aligned} \tag{1}$$

$$\begin{aligned}\text{downside}\Delta\text{CoES}_T^{i|N} &= E_T\left(R_{i,T+1:\,T+h} | R_{N,T+1:\,T+h} \leq \text{VaR}_{50}^N\right)\\ &\quad - E_T\left(R_{i,T+1:\,T+h} | R_{N,T+1:\,T+h} \leq \text{VaR}_{5}^N\right),\end{aligned} \tag{2}$$

where N denotes the number of industries; $R_{T+1}: T+h \geq \text{VaR95}$ denotes the extreme state of the upside risk accumulation phase, and $R_{T+1}: T+h \geq \text{VaR50}$ denotes the normal state of the upside accumulation phase; $R_{T+1}: T+h \leq \text{VaR5}$ denotes the extreme state of the downside risk mitigation, and $R_{T+1}: T+h \leq \text{VaR50}$ denotes the normal state of the downside risk mitigation.

2.2. Cross-Industrial Tail Risk Spillover Network. The available dataset is usually panel data of industry returns with high-dimensional properties when studying interdependencies among industries. We construct the long-term variance decomposition network ΔCoES-ENGDFM-LVDN that can solve the problem of high-dimensional data incidentally well. Second, this approach can study the correlation between financial and real sectors from the perspective of tail risk spillover, addressing the problem that methods such as correlation coefficients of returns and principal component analysis do not measure the contribution or exposure of individual institutions to systemic risk. The drawback that ΔCoVaR, MES, and other methods cannot capture the network effect of tail risk spillover is avoided. In addition, the method effectively bridges the previous deficiency of demonstrating risk only from the network of financial institutions. It should be noted that the results in this paper are mainly based on the heterogeneity part of $\Delta\text{CoES}^{i|N}$, and we argue about its rationality in 3.2. The specific process is as follows: extending the study of Barigozzi and Hallin [28], a two-step dynamic factorial procedure was used. First, the GDFM was applied to extract the common and idiosyncratic components from the tail risk data. Then, the EN model and the LVDN model are applied to identify the size and structure of tail risk spillover among industries.

Denote the two-factor process formed by N industries with tail risk data $\Delta\text{CoES}^{i|N}$ (including upside and downside) as

$$\Delta\text{CoES} = \left\{\Delta\text{CoES}_t^{i|N} : i \in N, t \in T\right\} = \chi_{it} + \xi_{it}, \quad i \in N,\ t \in T, \tag{3}$$

where ΔCoES satisfies second-order stationary, zero mean, and finite variance. ΔCoES is absolutely continuous with respect to the Lebesgue measure on $[-\pi, \pi]$. The qth eigenvector in the spectral density matrix diverges, and the qth+1st eigenvector is bounded. Hallin and Liška [35] prove that the horizontal market shock when the actual data are applied to the GDFM is unique, i.e., $q = 1$. Thus, there are autoregressive processes $A_i(L)\chi_{it} = \eta_{it} = (\eta_{1t}, \ldots, \eta_{Nt})', t \in T$ and $F_i(L)\xi_{it} = \nu_{it} = (\nu_{1t}, \ldots, \nu_{Nt})', t \in T$, where η_{it} and $\nu_{it}$are n-dimensional white noise processes, and $F_i(L)$ is a one-sided stable VAR filter. Barigozzi and Hallin [28] extracted the idiosyncratic components ξ_{it} of ΔCoES in $F_i(L)$ and used EN for sparse processing ξ_{it}, always admitting a Wold decomposition, which, after adequate transformation, yields the vector moving average (VMA) representation $\xi_{it} = D_i(L)e_{it}$. Comparing the above equations, we can obtain

$$D_i(L) = \left(F_i(L)\right)^{-1} R_i, \tag{4}$$

where the full-rank matrix R_i makes shocks $R_n^{-1}\nu_n = e_n$ orthonormal. R_i follows from a Cholesky decomposition of the covariance C_n^{-1} of the shocks [36], namely, $C_n^{-1} = R_n R_n'$. The residual centrality of the partial correlation network (PCN) based on C_n is ranked, so that the most correlated nodes are hit first. Decomposing R_i based on (4) yields the LVDN on the industry tail risk spillover. $w_{ij}^h = 100\left(\sum_{k=0}^{h-1} d_{k,ij}^2 / \sum_{l=1}^{n} \sum_{k=0}^{h-1} d_{k,il}^2\right), i, j = 1, \ldots, n$ means the dependence from contemporaneous to lagged h periods in the LVDN network. Taking the tail risk of each industry as node V, the industry tail risk spillover network $G(V, W)$ can be mapped.

2.3. Network-Associated Metrics. Network correlation indicators from Billio et al. [22] and Wanget al. [37] are borrowed to analyze the level and structure of the correlation of tail risk spillover across industries.

2.3.1. Degree of Association. The degree of association includes the degree of exit (δ_i^{To}) and the degree of entry (δ_i^{From}), which measures the external spillover effect of an industry in the network as well as its own spillover shock and is calculated as follows:

$$\begin{aligned} \delta_i^{\text{To}} &= \sum_{i=1, j \neq i}^{N} w_{ij}^h, \\ \delta_i^{\text{From}} &= \sum_{j=1, j \neq i}^{N} w_{ij}^h, \\ & j = 1, 2, \ldots, n. \end{aligned} \tag{5}$$

The out-degree portrays the sum of tail risk spillover caused by the tail risk spillover of an industry as a source. A higher degree of exit indicates that the industry is an active sender of tail risk spillover and the greater the tail risk spillover effect of the industry. The in-degree portrays the sum of tail risk spillover shocks to an industry as a recipient of tail risk spillover from other industries. A higher degree of entry means that the industry is more vulnerable to tail risk spillover from other industries. The total degree of association can be obtained by summing the out-degree and the in-degree, i.e., $\delta^{\text{Tot}} = 1/N \sum_{i=1}^{N} \delta_i^{\text{From}} = 1/N \sum_{i=1}^{N} \delta_i^{\text{To}}$.

2.3.2. Network Density and Closeness. The network density (ND) of N industries reflects the degree of connection between nodes in the network; the greater the density is, the closer the relationship between the nodes is. The ND indicator is expressed as

$$\text{ND} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \sum_{j \neq i} E_{i \longrightarrow j}. \tag{6}$$

Closeness (C) measures the average of the shortest distance between an industry node and all other reachable industry nodes in the network; the smaller the C value is, the shorter the distance between the industry and the reachable nodes is. It also means that the connection to the whole network is closer.

$$C(j) = \frac{1}{N-1} \sum_{i \neq j} d_{j \longrightarrow i}. \tag{7}$$

2.3.3. Relative Influence. Relative influence (RI) measures the relative size of the net external spillover of tail risk in an industry. The value of RI ranges from [−1, 1], and the machine formula is

$$\text{RI}(i) = \frac{\delta_i^{\text{To}}(i) - \delta_i^{\text{From}}(i)}{\delta_i^{\text{To}}(i) + \delta_i^{\text{From}}(i)}. \tag{8}$$

If the RI of an industry is positive (or negative), it means that its impact on other industries is greater (or less) than the impact of other industries on it; that is, the intensity of tail risk spillover from that industry to other industries is greater (or less) than the intensity of spillover from other industries to it. The greater the RI is, the greater the external spillover effect of tail risk in that industry is.

2.4. Sample Selection and Data Description. In the selection of industry indicators, we select 28 primary industry1 indices as the sample. The CSI 300 Index is a comprehensive stock price index that reflects the performance of China's stock market as a whole. Therefore, this paper calculates the $\Delta\text{CoES}^{i|N}$ of each industry index to the CSI 300 index to characterize the industry tail risk. The total sample range is December 2006–December 2020, the data frequency is monthly, and all data are from the Wind database. Considering the information available at each point in time and the calculation volume of the bootstrap method, this paper selects the last trading day data of each month and uses the sliding window algorithm to calculate the upside and downside $\Delta\text{CoES}^{i|N}$. The rolling window is set to 12 months. In addition, real-time monitoring of the intensity scale and path direction of tail risk spillover can measure the dynamics of the industry tail risk spillover relationship. We, therefore, combine the characteristics of China's financial market and use the structural breakpoint identification technique to exclude the impact of abnormal stock market fluctuations in 2015. Using a rolling analysis method, we select two subintervals of the total sample range, October 2008–March 2015 and July 2016–December 2020, to construct a phased risk network.

3. Results and Discussion

3.1. ΔCoES Measurement Results for Tail Risk. In this paper, we use ΔCoES to measure the level of tail risk spillover in each industry in China. Figure 1 gives the trend in the level of tail risk. There are two points that can be derived from the figure as follows. One is that the level of spillover during the accumulation of risk determines the level of spillover when the risk is mitigated. The upside ΔCoES is greater than the downside ΔCoES in most periods for each industry in the full sample interval. The reason is that the tail risk accumulates in the economic upward period and releases continuously in the economic downward period. Taking figure (a) as an example, the level of risk spillover from the mining industries increased more significantly during the adjustment period after the international financial crisis in 2008, the stock market volatility in 2015, and the intensification of international trade frictions and geopolitical conflicts in 2018 and 2019. Comparing Figures (a)-(f), we find that the level of tail spillover in each industry shows cyclical variation. The synergy of tail risks among industries suggests that the real sector, represented by mining and transportation, will also be hit as hard as the financial sector when a crisis occurs. However, it should be noted that the level of tail risk spillover also varies among industries. For example, the overall level of tail risk in the transportation sector began to increase significantly in October 2013, and the utilities upside tail risk had several significant increases in August 2009 and 2015 to 2016. Compared with other industries, the overall tail risk level of the financial sector is relatively stable, mainly concentrated in the range of 0.05–0.15.

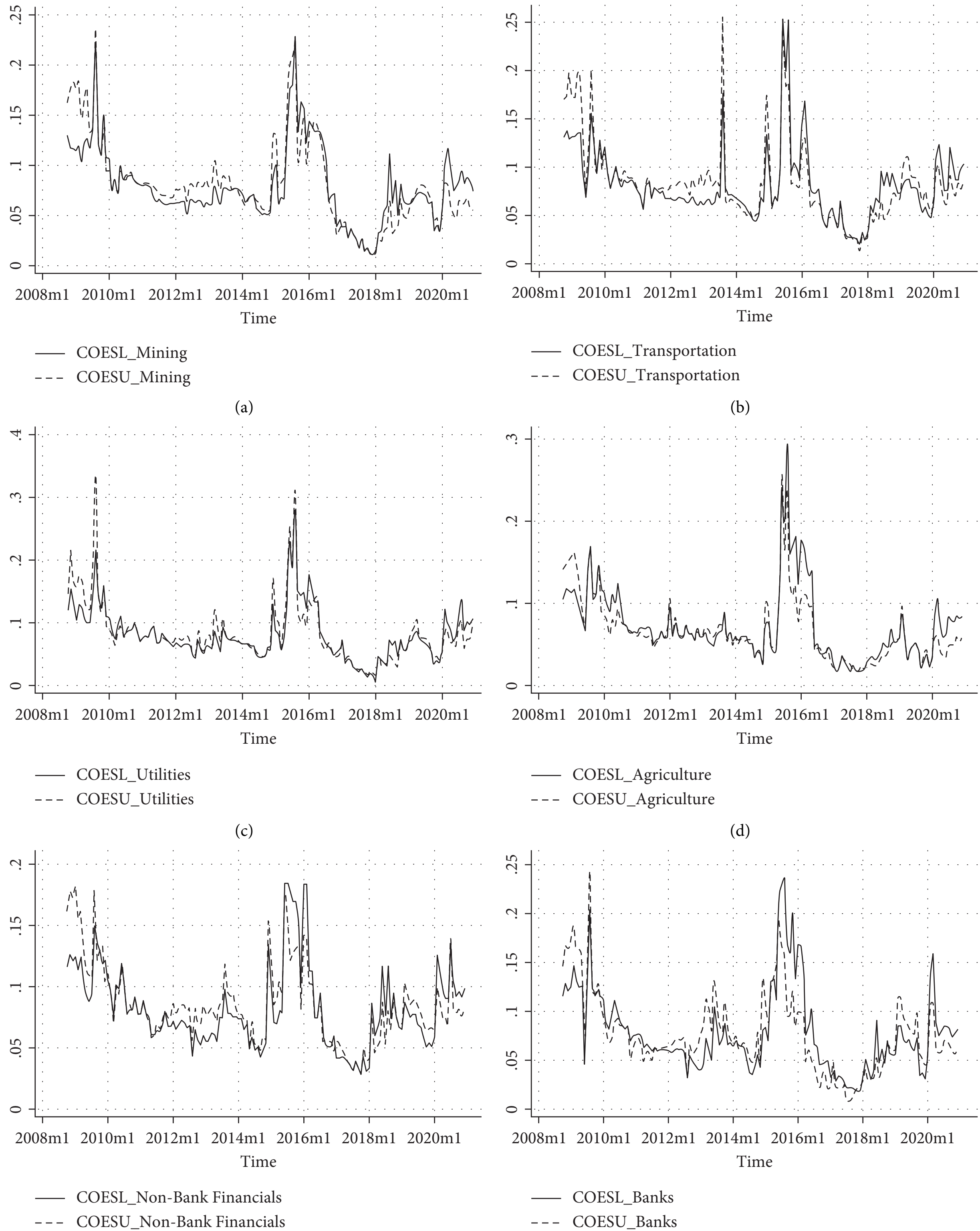
3.2. Sparsity Testing. In the spectral domain, partial spectral coherence (PSC) is strictly related to the coefficients of a VAR representation [38]. In line with the long-run spirit of the LVDN definition, and since volatilities have strong persistence, we first consider the PSCs at frequency $\theta = 0$, thus looking at long-run conditional dependencies. Selected percentiles of the distributions of the absolute value of the PSC entries for upside $\Delta\text{CoES}_T^{i|N}$ and idiosyncratic components ξ_{it} and the distribution of the absolute value of their differences are shown in Table 1. Both PSCs have many small (in absolute value) entries, which is consistent with our sparsity assumptions. Figures 2(a)-2(c) show the distributions of the absolute value of the PSC entries for upside $\Delta\text{CoES}_T^{i|N}$ and ξ_{it} and the distribution of the absolute value of their differences in turn. Similarly, Table 2 shows the distributions of the absolute value of the PSC entries for downside $\Delta\text{CoES}_T^{i|N}$ and idiosyncratic components ξ_{it} and the distribution of the absolute value of their differences. The two PSCs are shown in Figures 2(d) and 2(e). The above results suggest that the stochastic component also contains important dependencies after removing market-wide shocks. After ENGDFM processing, the form of factor plus sparse VAR can reveal the network internal dependencies. Therefore, we justify the application of ΔCoES-ENGDFM-LVDN to study the tail risk spillover among industries in terms of model treatment.

Left and middle panels: weights in absolute values below the 90th percentile in gray, weights above the 90th percentile in red, and weights below the 10th percentile in blue. Right panel: weights below the 90th percentile in gray, between the 90th and 95th percentiles in blue, and above the 95th percentile in red.

3.3. Association Level and Structure of Cross-Industrial Tail Risk Spillover in the Full Sample. Using China's 28 primary industries as network nodes, the cross-industrial tail risk spillover network is formed based on the estimated results of ΔCoES-ENGDFM-LVDN (as shown in Figure 3). Figures a and b represent the tail risk spillover relationships for each industry between the upside risk accumulation and downside risk release, respectively. We predict the outbreak of financial crisis and the realization of systemic risk release in the downside cycle through the risk-taking behavior and systemic risk accumulation process in various industries in the upside cycle. In theory, the upside risk spillover and right tail dependence are forward warning indicators of the downside and left tail dependence, where the size of the node indicates the size of the tail risk spillover shock to the industry, and the direction of the arrow between the nodes indicates the risk spillover path. The network indicators defined in the previous section are used to analyze the tail risk spillover among industries.

In the process of upside risk accumulation and downside risk mitigation, the network density index (ND) is 0.2248677 and 0.1891534, respectively. The total correlations are 36.17 and 49.41, respectively. This indicates that there is an overall persistent nonlinear spillover effect among industry tail risks in China with periodic variation characteristics. The total correlation of the upside risk accumulation process is smaller than that of the downside risk mitigation process, indicating that when the financial cycle is in the downside, the tail risks of the industry are more likely to hit other sectors along the risk network, showing more significant risk spillover effects. The reason for this is that when economic growth slows and investment and consumption are weak, the relative vulnerability of the industries tends to amplify the shock. A continued deterioration in economic conditions will also affect market stability and investor expectations, so risk contagion effects may differ significantly between economic ups and downs.

Based on the out-degree and in-degree indicators, we can calculate the spillover effect of industry tail risk in period h and analyze its role in the contagion chain. Table 3 collates the out-degree, in-degree, and RI indicators of tail risk spillover relationships for 28 primary industries, with



(a) (b) (c) (d) (e) (f)

Figure 1: Temporal variation characteristics of the ΔCoES.

columns (2)-(4) indicating the upside risk accumulation phase and columns (5)-(7) indicating the downside risk mitigation phase. In the upside risk accumulation process, the top 10 industry tail risks in descending order of out-degree are Textile and Apparel, Mining, Media, Agriculture, Food and Beverage, Utilities, Chemicals, Conglomerate, Transportation, and Leisure Services. They are active senders of risk spillover, and the spillover effect is

Table 1: The distributions of the absolute value of PSC for risk accumulation.

	Quartiles					
The absolute value of the PSC	50%	90%	95%	97.50%	99%	Maximum
$\lvert PSC_{\Delta CoES}(\theta = 0)\rvert$	0.124362	0.291909	0.323202	0.376626	0.428884	0.566802
$\lvert PSC_{\xi_n}(\theta = 0)\rvert$	0.117153	0.289620	0.328238	0.380161	0.468751	0.643701
$\lvert PSC_{\Delta CoES}(\theta = 0) - PSC_{\xi_n}(\theta = 0)\rvert$	0.043272	0.144979	0.170733	0.199930	0.228674	0.287758

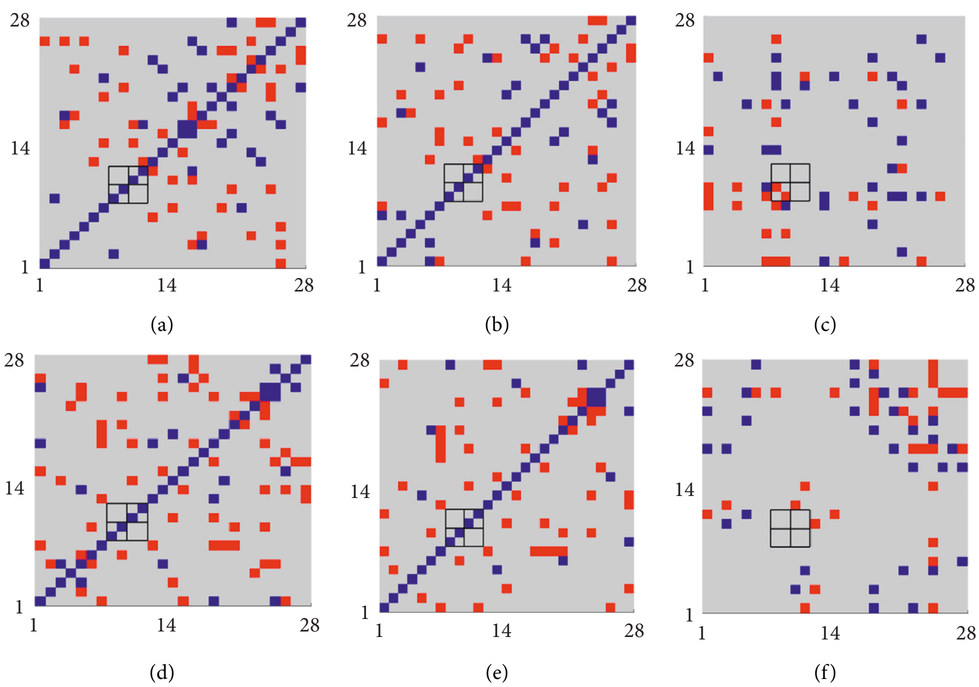
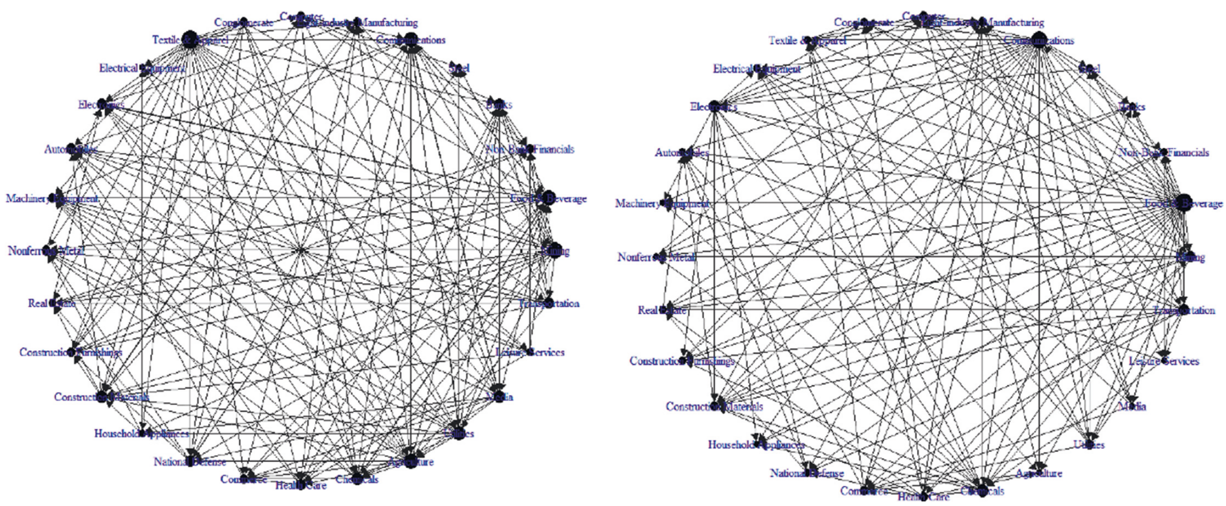


Figure 2: PSC in the process of risk accumulation and risk mitigation. (a) PSC of upside $\Delta CoES_T^{i|N}$. (b) PSC of upside ξ_{it}. (c) Absolute value of upside difference. (d) PSC of downside $\Delta CoES_T^{i|N}$. (e) PSC of upside ξ_{it}. (f) Absolute value of downside difference.

Table 2: The distributions of the absolute value of the PSC for risk mitigation.

	Quartiles					
The absolute value of the PSC	50%	90%	95%	97.50%	99%	Maximum
$\lvert PSC_{\Delta CoES}(\theta = 0)\rvert$	0.125615	0.313493	0.365495	0.435755	0.500213	0.592619
$\lvert PSC_{\xi_n}(\theta = 0)\rvert$	0.118030	0.293803	0.376495	0.436253	0.503897	0.626567
$\lvert PSC_{\Delta CoES}(\theta = 0) - PSC_{\xi_n}(\theta = 0)\rvert$	0.042004	0.109430	0.143421	0.177084	0.230884	0.324330

relatively strong. The top 10 industry tail risks of in-degree are Electronics, Machinery Equipment, Communications, Banks, Commerce, Automobiles, Construction Materials, Nonferrous Metal, nonbank finance, and Electrical Equipment. They are the primary recipients of the infection and are relatively vulnerable to spillover. In the downside risk mitigation process, the top 10 industry tail risks of out degree in order are Food & Beverage, Communications, Transportation, Electronics, Mining, Health Care, Chemicals, Utilities, Textile & Apparel, and Media. The top 10 industry tail risks of in-degree are construction materials, conglomerate, machinery equipment, chemicals, household appliances, nonbank finance, steel, light-industry manufacturing, commerce, and health care. From the above analysis, it can be seen that the nonbank financial industry is reflected in the in-degree ranking, indicating that whether in the upside risk accumulation or downside risk mitigation process, it has played the role of the recipient of tail risk spillover. Thus, it also indicates that the tail risk spillover from China's industry is reflected in the associated directions from the nonfinancial sector to the financial sector. Especially in the process of downside risk mitigation, more attention should be given to the ability of the nonbank financial sector to withstand tail risk spillover. We also found that the real estate industry ranked relatively low in both out-degree and in-degree values throughout the sample period, indicating that the process of analyzing tail risk spillover among industries cannot be prevented and resolved simply by the inherent impression of the industry.



(a) (b)

Figure 3: Full sample of China's cross-industrial tail risk spillover networks. (a) Upside risk accumulation process. (b) Downside risk mitigation process.

Table 3: Out-degree, in-degree, and RI indicator of cross-industrial.

Industry (1)	Upside risk accumulation phase			Downside risk mitigation phase		
	Out-degree (2)	In-degree (3)	RI (4)	Out-degree (5)	In-degree (6)	RI (7)
Mining	114.0545	17.4530	0.734570272	61.6501	32.8652	0.304552808
Transportation	38.4021	7.3969	0.676984214	66.7230	18.1311	0.572652353
Leisure services	26.1311	9.8383	0.452962796	12.8147	31.8501	−0.426183482
Media	86.6538	10.5619	0.782712052	17.7331	39.2600	−0.377710635
Utilities	54.2077	26.2984	0.346673109	29.1218	47.6602	−0.241442005
Agriculture	82.3181	36.6710	0.383624214	8.2766	52.5921	−0.728050706
Chemicals	53.5963	37.6067	0.175318794	37.6897	63.0075	−0.251425064
Health care	25.1435	23.4528	0.034790715	44.5775	55.4160	−0.108392045
Commerce	4.8575	52.3779	−0.83026239	10.1877	57.2267	−0.697758936
National defense	22.4761	33.6635	−0.199278228	9.3160	53.7339	−0.704488032
Household appliances	11.7469	28.1271	−0.410799017	0.0000	62.5923	−1
Construction materials	17.8422	48.3596	−0.460975381	16.5888	68.1793	−0.608607483
Construction furnishings	15.1180	23.3335	−0.213658765	15.7876	32.0357	−0.339752798
Real estate	5.4934	35.4223	−0.731477159	5.6138	52.0842	−0.805407466
Nonferrous metal	4.1867	47.8813	−0.839183376	2.2286	53.2019	−0.919589396
Machinery equipment	0.0000	60.7620	−1	0.0000	63.0327	−1
Automobiles	2.8404	48.3764	−0.88908327	0.0000	51.7961	−1
Electronics	16.9323	62.2757	−0.572459853	66.6504	44.8751	0.195249517
Electrical equipment	0.0000	43.5438	−1	0.0000	54.4843	−1
Textile and apparel	232.4349	0.0000	1	22.4120	46.8030	−0.352394712
Conglomerate	47.9072	33.7010	0.174078095	3.4964	64.7932	−0.897600806
Computer	11.7495	43.3565	−0.573567307	3.1802	51.7017	−0.884107511
Light-industry manufacturing	19.2448	37.9764	−0.327354197	7.2998	60.7444	−0.785439464
Communications	24.0707	60.1110	−0.428125115	239.5348	49.7838	0.655854826
Steel	7.0208	42.3321	−0.715485817	8.9733	62.0339	−0.747256616
Banks	3.8193	54.7705	−0.869625771	8.8933	51.3620	−0.704812689
Nonbank finance	4.5618	43.9214	−0.811819352	2.3020	62.3088	−0.928742563
Food and beverage	80.0580	43.2967	0.298012966	682.5041	0.0000	1
Total degree	36.1738			49.4127		

Columns (4) and (7) of Table 3 present the relative impact indicators for each industry, which measure the magnitude of the net spillover of tail risk in a given industry. During the upside risk accumulation process, the RI indicators of the top ten industries in terms of out-degree are all greater than zero, implying that they all have a positive net tail risk spillover. This can indicate that risks accumulate in several sectors during the upside and start to be mitigated during the downside. Taking into account the ranking by out-degree and the net spillover from the tail risk of the industry represented by RI, there are ten industries, Textile and Apparel, Media, Mining, Transportation, Leisure Services, Agriculture, Utilities, Food and Beverage, Chemicals, and Conglomerate, which become important sources of risk spillover in the process of risk accumulation during the sample period. In the downside risk mitigation process, combining out-degree values and the RI indicator reveals that Food and Beverage, Communications, Transportation, Mining, and Electronics are the main sources of net tail risk spillover. In addition, the number of net spillover industries has decreased during downside risk mitigation. The reason is that the abovementioned industries are important net spillover nodes and sources of risk, and their spillover is gradually mitigated in the process of downside risk mitigation.

A smaller tightness (C) indicates that the node is more closely connected to the whole network. During the accumulation of upside risk, the top 10 industries in order of C from smallest to largest are Machinery Equipment, Communications, Electrical Equipment, nonbank finance, Food and Beverage, Banks, Computer, Automobiles, Electronics, and Nonferrous Metal. During the downside risk mitigation process, the top 10 industries in ascending order of size C are Automobiles, Light-industry Manufacturing, Computer, Household Appliances, Banks, Electrical Equipment, Nonferrous Metal, Mining, nonbank finance, and Machinery Equipment. As shown in the columns of Table 4(2)-(3), certain industries, which are important sources of spillover, do not have high network tightness. In contrast, some risk sources that are not at the center of the risk network may have a stronger tail risk network propagation. It is worth noting that the industries with the same top rankings for closeness, out degree, in degree, and RI in the full sample interval are Machinery Equipment, Communications, Electrical Equipment, nonbank finance, Food and Beverage, Banks, Automobiles, and Nonferrous Metal. The eight industries mentioned above are at the center of the spillover association in the overall tail risk spillover network.

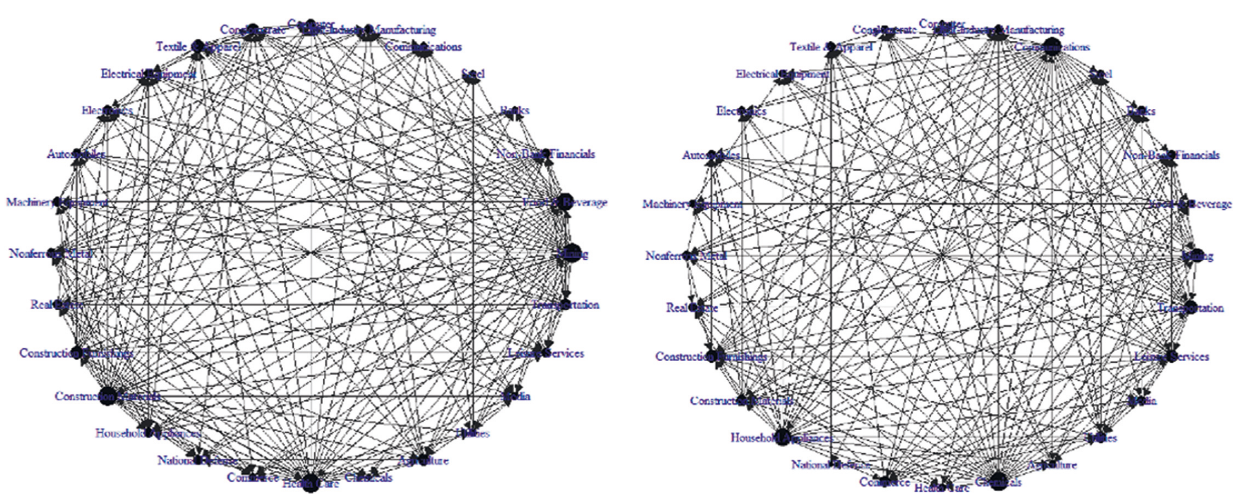
3.4. Dynamics of Cross-Industrial Tail Risk Spillover Correlation. The magnitude and direction of the association of cross-industrial tail risk spillover can change over time. The above examines the spillover of tail risk across industries in the network based on the full sample results but may miss important information changes, and regulators need to grasp the dynamic characteristics of the magnitude and path direction of correlation intensity across industries. This paper divides the sample interval into 2 different periods based on the characteristics of China's economic and financial market operations, combined with structural breakpoint2 identification. The two periods are October 2008–March 2015 (interval I) and July 2016–December 2020 (interval II), excluding the effect of the abnormal stock market volatility phase in 2015. Figure 4 gives the dynamic characteristics of the network correlation structure for the above two intervals.

In the process of risk accumulation in the interval of period I, the top 10 industry tail risks in order of out-degree are mining, food and beverage, health care, construction materials, construction furnishings, textile and apparel, transportation, agriculture, real estate, and nonferrous metals. The top 10 in-degree are communications, steel, automobiles, electrical equipment, chemicals, commerce, leisure services, national defense, electronics, and light-industry manufacturing. Columns 2–4 of Table 5 show the RI values, and the top ten industries, from largest to smallest, are mining, health care, food and beverage, construction materials, transportation, construction furnishings, textile and apparel agriculture, real estate, and nonbank finance. Closeness (C) ranking in order: communications, media, household appliances, light-industry manufacturing, national defense, electrical equipment, commerce, steel, electronics, and computer (as in column 4 of Table 4). In the process of risk mitigation, the top 10 industries ranked by tail risk out-degree ranking in order: chemicals, communications, transportation, household appliances, mining, leisure services, utilities, nonferrous metals, construction materials, and construction furnishings. The top 10 in-degree are steel, automobiles, computer, conglomerate, nonbank finance, electrical equipment, light-industry manufacturing, machinery equipment, food and beverage, and electronics. The RI ranking in order is chemicals, transportation, communications, mining, household appliances, leisure services, utilities, nonferrous metals, agriculture, and construction furnishings (as listed in columns 5–7 in Table 5). C is listed in ascending order as follows: light-industry Manufacturing, Food and Beverage, conglomerate, textile and apparel, nonbank finance, electrical equipment, electronics, automobiles, computer, and banks (as in column 5 of Table 4).

In the process of risk accumulation during the interval II period, the top 10 out-degree rankings of industry tail risk are mining, national defense, agriculture, chemicals, construction materials, electrical equipment, health care, construction furnishings, banks, and electronics. The top 10 in-degree rankings are machinery equipment, media, transportation, food and beverage, nonbank finance, light-industry manufacturing, household appliances, communication, leisure services, and automobiles. Columns 8–10 of Table 5 show the magnitude of RI, with the top ten in descending order: mining, agriculture, national defense, construction materials, chemicals, health care, electrical equipment, construction furnishings, banks, and commerce. C ranking in order: automobiles, machinery equipment, nonferrous metals, light-industry manufacturing, leisure services, household appliances, food and beverages, transportation, steel, and media (as in column 6 of Table 4). In the process of risk mitigation, the top 10 industry tail risks in order of out-degree are machinery equipment, transportation, chemicals, mining, conglomerate, media, utilities, agriculture, health care, and commerce. The top 10 in order of in-degree are nonbank finance, food and beverage, light-industry manufacturing, banks, computers, steel, communications, construction materials, national defense, and nonferrous metals. The RI ranking in order is machinery equipment, transportation, mining, chemicals, media, conglomerate, agriculture, utilities, health care, and commerce (as listed in Table 5, columns 11–13). The C ranking in order is nonbank finance, food and beverage, computer,

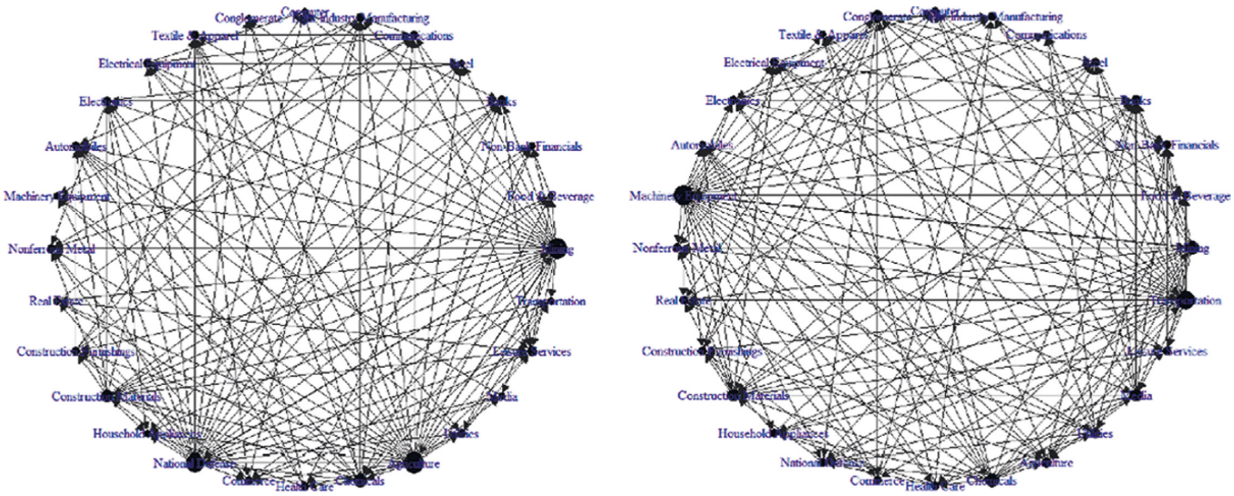
Table 4: Closeness values of China's industry.

Sample interval	Full sample interval		Interval 1		Interval 2	
Industry	Upside (2)	Downside (3)	Upside (4)	Downside (5)	Upside (6)	Downside (7)
Food and beverage	103	756	624	260	289	189
Communications	97	729	278	702	305	219
Transportation	145	702	625	387	291	258
Mining	124	171	625	378	702	260
Electronics	108	702	409	327	311	240
Health care	110	702	623	363	323	254
Utilities	113	186	464	375	319	257
Chemicals	116	182	464	756	312	261
Construction furnishings	118	197	622	358	334	235
Textile and apparel	756	187	541	298	315	226
Media	112	702	278	371	296	251
Leisure services	729	675	435	393	281	255
Construction materials	113	174	624	379	325	235
Commerce	111	193	383	372	308	255
National defense	115	621	381	361	702	247
Banks	104	166	569	357	308	227
Agriculture	115	648	541	371	703	250
Steel	114	182	390	360	293	239
Light-industry manufacturing	109	154	356	229	273	217
Real estate	110	176	595	358	323	239
Computer	107	156	409	341	336	211
Conglomerate	729	175	486	265	300	258
Nonferrous metal	108	168	516	369	264	237
Nonbank finance	101	173	567	308	299	182
Automobiles	107	143	567	335	216	211
Household appliances	123	158	303	702	284	248
Electrical equipment	100	167	381	326	675	234
Machinery equipment	79	173	541	366	254	243



(a) (b)

Figure 4: Continued.



(c) (d)

Figure 4: Cross-industrial tail risk spillover networks in China. (a) Upside risk accumulation process in interval I. (b) Downside risk mitigation process in interval I. (c) Upside risk accumulation process in interval II. (d) Downside risk mitigation process in interval II.

Table 5: Tail risk spillover network indicators among subsamples.

	Interval I						Interval II					
	Upside risks accumulate			Downside risks mitigated			Upside risks accumulate			Downside risks mitigated		
Industry (1)	Out-deg (2)	In-deg (3)	RI (4)	Out-deg (5)	In-deg (6)	RI (7)	Out-deg (8)	In-deg (9)	RI (10)	Out-deg (11)	In-deg (12)	RI (13)
Mining	350.61	13.23	0.9273	102.72	48.18	0.3614	1503.03	4.43	0.994	91.93	37.60	0.419
Transportation	67.29	20.95	0.5252	134.88	12.85	0.8261	0.0000	90.95	−1	162.33	55.24	0.492
Leisure services	7.81	81.43	−0.8249	65.19	56.08	0.0751	2.41	85.09	−0.945	9.83	59.43	−0.716
Media	0.0000	70.37	−1	14.94	63.59	−0.6195	2.11	92.19	−0.955	56.49	65.41	−0.073
Utilities	24.18	69.45	−0.4835	36.50	66.63	−0.2922	8.68	79.91	−0.804	35.38	68.41	−0.318
Agriculture	48.88	61.31	−0.1128	25.56	49.71	−0.3209	160.91	25.46	0.727	29.37	54.61	−0.301
Chemicals	3.63	81.78	−0.9150	1026.23	0.0000	1	48.41	83.70	−0.267	111.81	56.62	0.328
Health care	329.52	16.76	0.9032	16.53	63.15	−0.5851	21.41	49.21	−0.394	26.15	54.26	−0.35
Commerce	0.0000	81.43	−1	18.44	68.55	−0.5760	12.66	78.91	−0.723	22.90	57.74	−0.432
National defense	0.0000	80.79	−1	3.15	67.64	−0.9111	209.03	43.79	0.654	6.46	78.32	−0.848
Household appliances	0.0000	72.04	−1	126.73	67.12	0.3075	0.0000	85.76	−1	13.28	61.10	−0.643
Construction materials	294.46	51.61	0.7017	34.51	71.76	−0.3505	42.41	72.63	−0.263	22.68	80.22	−0.559
Construction furnishing	99.81	42.28	0.4049	28.36	56.16	−0.3289	19.00	83.91	−0.631	6.98	77.86	−0.836
Real estate	40.85	63.78	−0.2191	3.85	72.92	−0.8997	4.54	72.21	−0.882	2.61	75.06	−0.933
Nonferrous metal	29.45	78.37	−0.4537	35.41	66.59	−0.3056	0.0000	84.44	−1	10.76	77.92	−0.757
Machinery equipment	16.54	71.38	−0.6237	10.54	77.06	−0.7593	0.0000	95.88	−1	1225.46	7.21	0.988
Automobiles	24.88	84.78	−0.5463	2.62	86.32	−0.9411	0.0000	84.76	−1	0.0000	71.23	−1
Electronics	7.54	80.62	−0.8290	2.30	73.74	−0.9394	12.98	83.63	−0.731	13.38	71.42	−0.684
Electrical equipment	3.68	83.79	−0.9159	0.0000	79.23	−1	26.77	75.16	−0.475	8.23	65.99	−0.778
Textile and apparel	70.25	46.04	0.2082	6.60	70.73	−0.8292	9.17	77.62	−0.789	0.0000	71.22	−1
Conglomerate	25.88	77.18	−0.4977	0.0000	83.89	−1	0.0000	75.02	−1	60.02	70.03	−0.077
Computer	7.91	72.02	−0.8020	0.0000	85.70	−1	2.21	81.01	−0.947	5.46	86.55	−0.881
Light-industry manufacturing	0.0000	79.79	−1	0.0000	77.53	−1	10.82	89.12	−0.784	2.84	87.95	−0.937
Communications	0.0000	86.83	−1	141.45	64.11	0.3762	7.35	85.62	−0.842	0.0000	83.65	−1
Steel	0.0000	84.83	−1	2.30	88.86	−0.9495	0.0000	81.39	−1	2.68	84.51	−0.939
Banks	6.084	63.12	−0.8242	6.14	70.94	−0.8407	14.13	83.39	−0.71	2.28	87.56	−0.949
Nonbank financials	26.57	65.29	−0.4215	0.0000	81.18	−1	2.44	89.83	−0.947	0.0000	93.56	−1
Food and beverage	333.82	38.41	0.7936	0.0000	74.75	−1	4.53	89.97	−0.904	0.0000	88.61	−1
Total degree	64.99			65.89			75.89			68.90		

Table 6: Subsample index ranking.

	Interval 1 Upside	Interval 2 Upside
In-degree	Communications, steel, automobiles, electrical equipment, chemicals	Machinery equipment, media, transportation, food and beverage, nonbank financials
Out-degree	Mining, food and beverage, health care, construction materials, construction furnishings	Mining, national defense, agriculture, chemicals, construction materials
RI	Mining, health care, food and beverage, construction materials, transportation	Mining, agriculture, national defense, construction materials, chemicals
Closeness	Communications, media, household appliances, light-industry manufacturing, national defense	Automobiles, machinery equipment, nonferrous metal, light-industry manufacturing, leisure services
	Interval 1 downside	Interval 2 downside
In-degree	Steel, automobiles, computer, conglomerate, nonbank financials	Nonbank financials, food & beverage, light-industry manufacturing, banks, computer
Out-degree	Chemicals, communications, transportation, household appliances, mining	Machinery equipment, transportation, chemicals, mining, conglomerate
RI	Chemicals, transportation, communications, Mining, household appliances	Machinery equipment, transportation, mining, chemicals, media
Closeness	Light-industry manufacturing, food and beverage, conglomerate, textile & apparel, nonbank financials	Nonbank financials, food and beverage, computer, automobiles, light-industry manufacturing

automobiles, light-industry manufacturing, communications, textile and apparel, banks, electrical equipment, and construction furnishings (as in column 7 of Table 4).

To facilitate the analysis, we briefly present the above results in Table 6. They show that the level of risk spillover in different industries differs from the average cross-industrial risk spillover in the overall market in different intervals. The cross-sectional dimension allows us to compare the differences in spillover effects between the upside risk accumulation and downside risk mitigation phases within the same sample interval and analyze the accumulation of risk spillover levels from normal to extreme states. The time dimension allows for a longitudinal analysis of the evolution of the industry tail risk spillover relationship across the intervals. It is possible to compare the evolution of risk spillover within the same risk phase (upside risk accumulation or downside risk mitigation) across sample intervals.

First, the differences in tail risk spillover effects among industries are compared. In interval I, the senders of risk spillover during the upside risk accumulation process include the tail risk of the real estate industry, and the receivers of risk spillover do not have banks or nonbank financial industries. Nonbank finance appears in the in-degree ranking as the receivers of tail risk spillover during the downside risk mitigation process. There are no estimates of tail risk in the real estate industry in either the full sample interval or the sample interval II out-degree ranking, indicating that the impact of tail risk in the real estate industry is large in the earlier period. The impact of tail risk accumulation within the real estate industry in China has gradually decreased in recent years with the regulation of this industry. The risk spillover senders and receivers in Interval II are more likely to reflect the tail risks of industries involving emerging sectors of strategic importance, such as communications, computers, and health care, indicating that the impact of strategic emerging industries on the economic and financial system is of increasing concern in the process of structural transformation and upgrading of China's industries. In Interval II, in terms of closeness, tail risks in the nonbank financial industry are not at the center of the network during the upside risk accumulation phase but evolve into an important network center during the downside risk mitigation phase, playing an important role in the risk spillover contagion chain.

Second, the evolution of the cross-industrial tail risk spillover is compared across different intervals. In the process of upside risk accumulation and downside risk mitigation, the network density indicators ND in sample intervals I and II are 0.2592593 and 0.2301587 and 0.1931217 and 0.207672, respectively. The total correlations are 64.99 and 65.89 and 75.89 and 68.90, respectively; thus, the nonlinear effects and cyclical changes of tail risk spillover among industries still exist. Regardless of the upside risk accumulation or downside risk mitigation process, the total correlation in interval II is greater than that in interval I. This indicates that the impact of tail risk spillover in China has been gradually expanding in the cross-industrial range in recent years from the vertical time dimension. In the interval I time period, the total correlation of the upside risk accumulation process is smaller than the total correlation of the downside risk mitigation process, while in the interval II time period, the result is the exact opposite. The total correlation of the upside risk accumulation process shifts to be larger than the total correlation of the downside risk mitigation process, indicating that the downside risk is not fully mitigated in the process of expanding the impact of tail risk spillover in recent years. In addition, in the downside and upside risk phases of the two sample subregions, the tail risks of industries such as mining, transportation, utilities, and agriculture in the nonfinancial sector are among the stable risk spillover senders. They provide basic services and production materials supply for other sectors while generating more obvious risk shocks to other industries. The tail risks of the communications, health care, computer, and other industries are gradually rising in the network. This conclusion forms a synthesis of established studies related to cross-industrial risk spillover and an extended validation of them. It is worth noting that although the nonbank financial industry is not in the ranking of risk spillover senders, the in-degree ranking of the industry has improved more significantly in recent years. During the downside risk mitigation phase of Interval II, it is not only the top-ranked tail risk spillover recipient, but also in the center of the network in terms of closeness, which again confirms the characteristics of tail risk spillover from the nonfinancial sector to the financial sector. Based on the fact that China's nonbank financial industry is not the sender but the receiver of tail risk spillover, it is more important to pay attention to the increase in risk exposure of the nonbank financial sector and strengthen its ability to bear tail risk spillover. At the same time, it is also necessary to pay attention to the risk-sending effect presented by the Bank sector during the upside risk accumulation phase and the role it played in promoting risk accumulation.

Finally, the evolution of risk spillover within the same risk stage in different sample intervals is compared. Based on the estimation results, it is found that the total correlation within interval II during the accumulation of upside risk is significantly larger than the total correlation in interval I. This indicates that the upside risks have accumulated faster in recent years, but thanks to effective regulation, the downside risk mitigation is gradually resolved and does not show an accelerating trend of mitigation. That being said, there is still a need to focus on the impact of upside risks.

4. Conclusion

This paper applies the ΔCoES-ENGDFM-LVDN method to construct a tail risk spillover network with periodic properties among China's industries and investigates the level and structure of association of the tail risk spillover network, as well as the role of each industry in the risk contagion chain. We identify the characteristics and the dynamic contribution of each industry in the tail risk transmission chains. On the one hand, this paper analyzes tail risk in-degree, out-degree, RI, and closeness indicators based on cross-sectional dimensions for the full sample period and finds that there is variability in the level of tail risk spillover among industries. For example, the real estate industry, an important source of risk inherently perceived, has ranked relatively poorly in recent years in terms of out and in indicators. The risk spillover indicators in both sample subintervals show that the mining, transportation, utilities, and agriculture sectors in the nonfinancial sector are stable sources of risk. The nonbank financial industry is the recipient of tail risk spillover and gradually evolves into an important network center in the downside risk mitigation phase. This indicates that the tail risk spillover in China's industries is reflected in the direction of correlation from the nonfinancial sector to the financial sector. On the other hand, the in-degree ranking of the nonbank financial industry has improved significantly in recent years. It becomes the most central industry in the tail risk network and is very closely linked to other industries. The reason for this is likely due to the rapid growth of China's nonbank financial business, whose regulatory avoidance, high leverage, and maturity mismatch characteristics have led to increased vulnerability of the nonbank finance. In addition, the real estate industry had a large tail risk impact in the early period (interval I), but the output effect of tail risk in the real estate industry is gradually weakening as national regulations are gradually taking effect (interval II). At the same time, emerging industries in China, such as communications, health care, and computers, have been more represented among the senders and receivers of tail risk since 2016. This also indicates that emerging industries in China are increasingly worthy of attention.

The network density and the total degree of correlation indicators show that there are a continuous nonlinear spillover effect and an obvious cyclical characteristic among China's industry tail risk as a whole. The spillover effect of industry tail risk during the downside risk mitigation process is more pronounced, but the gradual growth of the total degree of the upside risk accumulation process has exceeded the total degree of the downside. This suggests that although the impact of cross-industrial tail risk spillover in China has gradually expanded, due to effective regulation, it has not been released sharply.

Based on the above findings, this paper puts forward the following policy recommendations. First, the regulator should expand the scope of concern, not only focusing on the financial sector, but also paying attention to the tail risk spillover effect of the nonfinancial sector. Focus more on stable risk spillover sectors represented by mining, transportation, utilities, and agriculture. At the same time, it is important to avoid falling into the rigidity of thinking and not simply focusing on risk prevention in traditional high-risk spillover industries, such as the real estate industry. Depending on the role and status of different industries in the tail risk spillover process, different regulatory policies should be selected in a targeted manner. When establishing a risk warning system related to each industry in China, the different systematic contributions of each industry in the risk transmission chain should be taken into account comprehensively. A dynamic adjustment mechanism should be introduced to lay the foundation for a more reasonable prevention of tail risk spillover. Second, as the nonbank finance has long been in the position of the recipient of tail risk spillover, improving the ability of the nonbank finance to resist risks, reducing the vulnerability of the industry, and regulating its operation are the focus of risk prevention. Third, with the improvement of capital structure and industrial restructuring, the importance of emerging industries in the risk spillover network is gradually increasing, and more attention should be given to the risk contagion of such industry fluctuations for the overall industries and preventing tail risk transmission from the nonfinancial sector to the financial sector. [39].

Data Availability

Data are available upon request to corresponding author.

Additional Points

(1) Tail risk spillover in China's industries has both periodicity and variability characteristics. (2) Cross-industrial tail risks spillover from the nonfinancial sector to the

financial sector in China. (3) The impact of the tail risk of emerging industries on the whole economic and financial system is gradually increasing in China. (4) The impact scope of cross-industrial tail risk spillover in China has gradually expanded, but the downside risk has not been released sharply. Network effects and characteristics of cross-industrial tail risk spillover in China.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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