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Connectedness and systemic risk spillovers analysis of Chinese sectors based on tail risk network

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ABSTRACT

This paper investigates the systemic risk spillovers and connectedness in the sectoral tail risk network of Chinese stock market, and explores the transmission mechanism of systemic risk spillovers by block models. Based on conditional value at risk (CoVaR) and single index model (SIM) quantile regression technique, we analyse the tail risk connectedness and find that during market crashes, stock market exposes to more systemic risk and more connectedness. Further, the orthogonal pulse function shows that Herfindahl-Hirschman Index (HHI) of edges has a significant positive effect on systemic risk, but the impact shows a certain lagging feature. Besides, the directional connectedness of sectors shows that systemic risk receivers and transmitters vary across time, and we adopt PageRank index to identify systemically important sector released by utilities and financial sectors. Finally, by block model we find that the tail risk network of Chinese sectors can be divided into four different spillover function blocks. The role of blocks and the spatial spillover transmission path between risk blocks are time-varying. Our results provide useful and positive implications for market participants and policy makers dealing with investment diversification and tracing the paths of risk shock transmission.

1. Introduction

In recent years, financial markets have become extremely volatile, especially the global financial crisis in 2008 and the continued global plunge in global stock markets caused by the COVID-19 in 2020. This has drawn lots of attention from academia trying to measure systemic risks and grasp the system risk spread across sectors or markets. There is some evidence that financial systemic risk threatens “the function of a financial system” and impairs “the public confidence or the financial system stability” (Billio et al., 2012). It is widely observed that systemic risk spillovers have a significant “production-contagion-re-contagion” patterns. For the interconnectedness within a market, once one sector encounters a risk shock, the risk will affect other sectors through strong linkages and contagion mechanisms, and even spread to the entire financial markets. In this context, investigation into the connectedness among financial markets and the systemic risk spillovers contagion mechanism across sectors or markets become important and necessary, which is helpful for regulators to identify sources of risks and formulate intervention strategies, and for investors to make smarter portfolio strategies.

The complex relationship between financial markets and their internal elements is the carrier of systemic risk transmission, and their connectedness patterns or structures play an important role in the formation and infection process of systemic risks. Moreover,
the concept of systemically important financial institutions (SIFIs) can be extended to broader markets or sectors. Some scholars find that sectors have different response to shocks due to their own market and sectoral heterogeneity and risk features (Ewing, 2002; Ranjeeni, 2014; Yang et al., 2016; Wu et al., 2019). For stock market participants, sectoral indexes can be used as a significant indicator to access portfolio performance. Identifying which sector is the most influential and how systemic risks spillover among sectors is essential for effective risk management and optimal portfolios. Therefore, in addition to cross-institution risk spillovers, cross-sector and cross-market risk transfer has become increasingly prominent. It not only greatly increases the probability of cross-contagion of financial risks, but may also trigger broader systemic risks. Referring to the knowledge of SIFIs, this paper measures the systemic risk of each sector in Chinese stock market, analyzes the spatial connectedness of various sectors to determine which sectors play a leading role in risk spillover or market co-movements, and explores the risk spillover transmission paths. The results of this study could manage the systemic risk and preserve financial stability, which in turn, contribute to the smooth functioning of the real economy.

Although its (cross-sectors) great important, the existing literature on this topic is relatively scarce. This study we first develop and apply the tail risk network with the single-index generalized quantile regression model of Hardle et al. (2016), which takes into consideration non-linearity relationships and variable selection. Further, we investigate the tail risk network topology and its dynamic changes to analyze the spatial connectedness of 24 Chinese sectors during 2007–2018. In order to understand the impact of network connectivity on systemic risk, we draw on the orthogonal pulse function to find that HHI of edges has a significant positive effect on systemic risk. Second, we adopt PageRank index to identify systemically important sector. It is observed that although the systemically important industries are time-varying, and the Utilities and Financial sectors (including banks, insurance and diversified finance) still should be received more attention. Finally, we innovatively use block models to assess the roles of different spillover blocks, and excavate the transmission paths of risk spillover in different blocks.

The remainder of the paper is organized as follows. In Section 2 related literature about our study is outlined. Section 3 shows the data and methodology. Section 4 is the empirical results. Section 5 presents our conclusion.

2. Related literature

Systemic risk threatens the stability and functioning of financial markets when the stock market is confronted with sharp downturn, reduced with market confidence and willingness of risk taking. And it is considered to be the risk of causing a large number of participants in the market to suffer serious losses at the same time and quickly spread into the system (Benoit et al., 2017). A number of researchers have discussed the measurement of financial system’s systemic risk and the macro-prudential risk management approaches (Laevens et al., 2016; Acharya et al., 2012). The relevant literature in this filed can be roughly divided into four categories: the first is conditional value-at-risk (CoVaR). Adrian and Brunnermeier (2007) put forward the CoVaR, defined as the VaR of the financial system when a single market or sector encounters some specific events. And then they proposed a measure of systemic risk, ΔCoVaR (Adrian and Brunnermeier, 2007), which is defined as the difference between CoVaRs when a sector is and is not under turmoil. Girardi and Ergun (2013) used CoVaR approach to measure the systemic risk contribution of four financial sectors composed by lots of institutions, and investigated the relationship between institutional characteristics and systemic risk contributions. The second method emphasizes the default probability of financial institutions through the interrelationships between financial assets. For example, principal component-based analysis, e.g. Kritzman et al. (2011), Bisias et al. (2012), Rodriguez-Moreno and Pena (2013) and others; cross-correlation coefficient-based analysis, e.g. Huang et al (2009), Patro et al. (2013). The third category uses the copula function to calculate the systemic risk with biased tail of stock market. Krause and Giannante (2012) adopted copula function to calculate the nonlinear correlation of time series and establish an interbank lending network. The results show that externally failed banks can trigger potential banking crisis and analyze the spread of risks within the banking system. The last category looks at an institution’s expected equity loss when the financial system is suffering losses. Acharya et al. (2017) proposed marginal expected shortfall (MES) and systemic expected shortfall (SES), which are two systemic risk measures. Further approaches take into the information of market capitalization and liability, such as, the SRISK (Brownlees and Engle, 2017) and the component expected shortfall (CES) (Banulescu and Dumitrescu, 2015). Both the SRISK and CES methods especially focus on the inter-dependence between a financial institution and the financial system, and ignore the interconnectedness among financial agents from a whole system perspective.

However, as pointed out by Bluhm and Krahnen (2014) macro-prudential monitoring is still at a very early stage, quantifying the magnitude of systemic risk and identifying the transmission paths need more scientific analysis. To do so we apply network methodology to quantify the interconnectedness among sectors in financial system. Network theory has always been a leading tool for analyzing the intricate connectedness relationship because it can conquer the “dimension barrier” of multivariate econometric models and simplify complex financial systems (Acemoglu et al., 2015; Battiston et al., 2016; Huang et al, 2018). And in financial network, financial entities (e.g. institutions, sectors and markets) are abstracted to nodes, and correlations among agents are abstracted to edges. The early literature on classic network construction methods is correlation-based networks, such as the minimal spanning tree (MST) (Mantegna, 1999), the planar maximally filtered graph (PMFG) (Tumminello et al., 2005) and the partial correlation-based network (Wang et al., 2018). The main disadvantage of the correlation-based network is that the economic or statistical meanings of their topological constraints are unclear (Onnela et al., 2003; Kenett et al., 2015; Zhang et al., 2019). More recently, several econometric-based networks have been constructed to uncover information spillover paths and contagion sources (Výrost et al., 2015; Lyocsa et al., 2017; Belke and Dubova, 2018). The extensively econometric-based networks are classified into three groups: (i) mean-spillover network (also called Granger-causality network), which is proposed by Billio et al. (2012); (ii) volatility spillover network, e.g., the variance decomposition frame-based network of Diebold and Yilmaz (2014), and the GARCH
model-based network of Liu et al. (2017); (iii) risk spillover network, which major includes tail-risk driven network of Hautsch et al. (2015) and Hardle et al. (2016), and extreme risk network of Wang et al. (2017). Of course, many studies have discussed the application of spillover networks. This study is distinguished from existing information spillover literature by focusing on systemic risk spillover, especially tail risk spillover.

The last strand is associated with the tail risk spillover network and its applications. Hautsch et al. (2015) used the least-absolute shrinkage and selection operator (LASSO) method to build a tail risk network for the financial system, and evaluated the systemic importance of financial firms. The tail-event driven NETwork (TENET) of Hardle et al. (2016) is based on CoVaR of Adrian and Brunnermeier (2007) and is constructed by semiparametric quantile regression framework that considers non-linearity and variable selection. They have discovered the asymmetry and non-linear dependency structure between financial institutions and identified systemically important institutions. Wang et al. (2017) applied CAViaR tool and Granger causality test to measure systemic risk spillovers, and then proposed an extreme risk spillover network for studying the interconnection among financial institutions. Wang et al. (2018) constructed dynamic tail risk networks to investigate the interconnectedness and systemic risk of Chinese financial institutions. The findings show that some small companies have shown systemic importance due to their high level of incoming (outgoing) connections. Verma et al. (2019) applied the TENET risk model to quantify the systemic risk of Indian banks and distinguished the systemically important banks. Huang and Wang (2019) adopted TENET tool to examine the tail risk spillover effects in China’s financial network and analyzed the impact of financial markets on Chinese economic output. Chen, Härdle, and Okhrin (2019) extended the tail event driven network to tail event driven network quantile regression (TENQR) model which addresses the interdependence, risk propagation and systemically important of financial institutions.

Our work contributes to the literature in three major aspects. First, we analyze the characteristics of spatial connectedness and systemic risk spillovers of tail risk network using sectoral data in Chinese stock market. We extend the literature on interconnectedness and systemic risk of sectors level data while extant literature generally focuses on the financial institutions data. Second, we innovatively adopt orthogonal pulse function to explore the impact of network connectivity on systemic risk of financial system. Besides, we employ PageRank index to identify systemically important sectors that spread systemic risk spillovers to entire system. Third, we apply block model in our study to assess the roles of different spillover blocks of 24 sectors in risk contagion process, and excavate the tail risk transmission paths and contagion mechanisms. The existing literature focuses more on the network topology and the identification of important financial institution nodes in the financial institution network, but lacks the risk propagation mechanism analysis. Importantly, it is necessary to clarify how system risk transfers across sectors.

3. Data and methodology

3.1. Data

In order to analyze the systemic risk spillovers and its interconnectedness across Chinese sectors, we select the weekly closing prices $P_{it}$ of 24 sectors in China’s stock market (name abbreviations of 24 industries are seen in Appendix Table A1). The sample data

| Industries                                   | Mean         | Max          | Min          | Std. Dev.  | JB           | Obs. |
|----------------------------------------------|--------------|--------------|--------------|------------|--------------|------|
| Energy                                       | -0.0001      | 0.1544       | -0.1938      | -0.1938    | 174.250***   | 613  |
| Materials                                    | 0.0009       | 0.1698       | -0.2641      | -0.2641    | 211.764***   | 613  |
| Capital goods                                | 0.0015       | 0.2366       | -0.2599      | -0.2599    | 331.101***   | 613  |
| Business and professional services           | 0.0017       | 0.2392       | -0.3125      | 0.3125     | 451.337***   | 613  |
| Transportation                               | 0.0004       | 0.1497       | -0.2297      | -0.2297    | 227.475***   | 613  |
| Automotive and automotive parts              | 0.0021       | 0.1618       | -0.2057      | -0.2057    | 222.675***   | 613  |
| Durable consumer goods and clothing          | 0.0026       | 0.1622       | -0.1848      | -0.1848    | 172.963***   | 613  |
| Consumer services                            | 0.0016       | 0.1827       | -0.2112      | -0.2112    | 187.767***   | 613  |
| Media                                        | 0.0003       | 0.1879       | -0.2231      | -0.2231    | 115.566***   | 613  |
| Retail                                       | 0.0011       | 0.1967       | -0.3014      | -0.3014    | 460.467***   | 613  |
| Food and major articles retail               | 0.0018       | 0.2195       | -0.2697      | -0.2697    | 439.299***   | 613  |
| Food, beverages and tobacco                  | 0.0022       | 0.1568       | -0.1824      | -0.1824    | 100.516***   | 613  |
| Home and personal items                      | 0.0021       | 0.2022       | -0.2446      | -0.2446    | 272.807***   | 613  |
| Healthcare equipment and services            | 0.0030       | 0.2107       | -0.2358      | -0.2358    | 219.750      | 613  |
| Pharmaceutical, Biotechnology and Life Sciences | 0.0030      | 0.1805       | -0.1637      | -0.1637    | 127.573      | 613  |
| Bank                                         | 0.0012       | 0.1718       | -0.1832      | -0.1832    | 159.741***   | 613  |
| Diversified finance                          | 0.0008       | 0.3046       | -0.2027      | -0.2027    | 293.215***   | 613  |
| Insurance                                    | 0.0008       | 0.1984       | -0.2135      | -0.1919    | 39.153***    | 613  |
| Real estate                                  | 0.0013       | 0.1907       | -0.2399      | -0.2399    | 123.128***   | 613  |
| Software and service index                   | 0.0027       | 0.1660       | -0.2388      | -0.2388    | 143.755***   | 613  |
| Technical hardware and equipment             | 0.0021       | 0.2003       | -0.2424      | -0.2424    | 232.293***   | 613  |
| Semiconductor and semiconductor production equipment | 0.0010   | 0.1882       | -0.2732      | -0.2732    | 162.346***   | 613  |
| Utilities                                    | 0.0012       | 0.1295       | -0.2732      | -0.2732    | 1071.416***  | 613  |
| Telecommunications services                  | 0.0003       | 0.1716       | -0.2225      | -0.2225    | 109.378***   | 613  |

Notes: *** denote significance at 1%.
ranges from January 4, 2007 to December 31, 2018 (total of 613 trading weeks), and the industry classification data is available from Wind database. Our analysis centralizes the weekly returns of each sector, which is defined as
\[ R_{i, t} = \ln \left( \frac{P_{i, t}}{P_{i, t-1}} \right) \]

Table 1 presents the descriptive statistics for weekly returns of 24 sectors during the sample period. Note that maximum of return series except for PBLS and DF, is less than the absolute minimum, implying that there is extreme risk in the left-tail of the yield distribution. Besides, the JB statistics for each sector is significant at 1% level that rejects the null-hypothesis of Gaussian distribution for the series. Thereby, we can use single-index model (SIM) quantile regressions to estimate the CoVaR.

Apart from the closing price data, motivated by Wang et al. (2018), we also collect five macro state variables and four internal variables. The macro state variables contain the weekly market returns, the market volatility, the real estate sector returns, the credit spread and liquidity spread, which depict the economic situation. The internal variables contain the size, the turnover rate, the P/E ratio and P/BV, which reflect the influence of industry from the fundamental characteristics. The detailed definition of these variables can be seen from Table 2.

### 3.2. Methodology

#### 3.2.1. Tail risk network

In this paper, we adopt the novel TENET framework proposed by Hardle et al. (2016) to measure the tail risk interconnectedness among various industries and build dynamic evolution tail risk network in China’s stock market. As we all known, Adrian and Brunnermeier (2016) only perform linear interaction between two financial institutions, however, Chao et al. (2015) find that any two interacting financial assets show non-linear dependency, especially in uncertain economic periods. Therefore, accounting for non-linearity dependency, Hardle et al. (2016) develop the bivariate model to a high-dimensional state and solve the variable selection problem by single-index quantile regressions. Accordingly, we also exert three estimation steps to complete tail risk network’s construction.

First step, the VaR for each industry \( i \) at \( \tau \in (0, 1) \) quantile level should be first estimated by using linear quantile regression. Given the return \( R_{i, t} \) of industry \( i \) at time \( t \):

\[ P( R_{i, t} \leq VaR_{i, t, \tau} ) = \tau \]

\[ R_{i, t} = \alpha_{i} + \chi M_{i, t-1} + \epsilon_{i, t} \]

\[ VaR_{i, t, \tau} = \tilde{\alpha}_{i} + \tilde{\chi} M_{i, t-1} \]

where \( M_{i, t-1} \) represents the macro state variables, \( \chi \) is the estimated parameters.

Second step, the CoVaR is the basic element of the network, and it can reflect the systemic (tail) risk interconnections of sectors. The tail risk interconnectedness from one industry to another in the tail risk network stands for the systemic risk contagion and network spillovers. Thus the CoVaR should be second estimated. We perform a risk connectedness analysis by accounting for non-linear dependency in high dimensional variables, and adopt SIM quantile regression technique to gain the systemic risk contribution due to a change in the relevant industry. It is obtained via:

\[ R_{i, t} = \beta_{i}^{T} \tilde{Z}_{i, t} + \xi_{i, t} \]

\[ CoVaR_{\tilde{M}, t, \tau} \equiv g \left( \tilde{\beta}_{\tilde{M}}^{T} \tilde{Z}_{t, \tau} \right) \]

The detailed statistical method of TENET is given in Härndle et al. (2016)
\begin{equation}
\frac{\partial \hat{\beta}_{j_s}^T}{\partial Z_{j_s}} = \frac{\partial g\left(\hat{\beta}_{j_s}^T Z_{j_s}\right)}{\partial Z_{j_s}} = g\left(\hat{\beta}_{j_s}^T Z_{j_s}\right) \frac{\partial Z_{j_s}}{\partial Z_{j_s}} = g\left(\hat{\beta}_{j_s}^T Z_{j_s}\right) \delta_{j_s} \tag{6}
\end{equation}

where $Z_{j_s} \equiv [R_{j,1}, M_{j,1}, F_{j,1}]$ defines the information set; $R_{j,1} = [R_{1,1}, R_{2,1}, \ldots, R_{N,1}]$ is the independent variables including the returns of all industries apart from industry $j$; $N$ denotes the number of sectors; $F_{j,1}$ is the internal features of every industry, i.e., size, turnover rate, P/E ratio, P/BV; $\beta_{j_s}^T \equiv \left\{\beta_{j_1}, \beta_{j_2}, \beta_{j_3}\right\}^T$ is the parameters, and $\beta_{j_s}^T = \left\{\hat{\beta}_{j_1}, \hat{\beta}_{j_2}, \hat{\beta}_{j_3}\right\}^T$.

The CoVaR$_{\text{NET}}$, represents network risk triggered by tail-event, which includes of all other relevant industries on industry $j$ and the non-linearity that is reflected by the function $g(\cdot)$, $\hat{\beta}_{j_s}$ is quantifying the marginal effect of covariates, and $\hat{\beta}_{j_s} = [\hat{\beta}_{j_1}, \hat{\beta}_{j_2}, \hat{\beta}_{j_3}]^T$ is the componentwise expression, where $\hat{\beta}_{j_i} = |\hat{\beta}_{j_i}| 1 \leq i \leq N, i \neq j$ could reflect the risk spillover effects among sample industries. Note that we only centralize the partial derivatives of industry $j$ on the other industries ($\hat{\beta}_{j_i}$) in given network. Additionally, we can also use rolling window estimation to estimate all parameters.

Last step, the directed tail risk network should be constructed. It is denoted as graph $G(V, E)$ with a set of nodes $V = \{v_1, v_2, \ldots, v_N\}$ and a set of edges $E$. The adjacency matrix $G_s$ with all linkages at window $s$ is to be:

\begin{equation}
\begin{pmatrix}
0 & |\beta_{j_1}^z| & \beta_{j_1}^z & \cdots & \beta_{j_1}^z \\
|\beta_{j_2}^z| & 0 & |\beta_{j_2}^z| & \cdots & \beta_{j_2}^z \\
\cdots & \cdots & \cdots & \cdots & \cdots \\
|\beta_{j_N}^z| & |\beta_{j_N}^z| & \cdots & 0
\end{pmatrix}
\end{equation}

Out-strength $\sum_{j=1}^{N} |\beta_{j_i}^z|$

\begin{equation}
\sum_{j=1}^{N} \sum_{j=1}^{N} |\beta_{j_i}^z| \tag{7}
\end{equation}

where $v_i$ denotes the name of industry $i$. The absolute value of $\beta_{j_i}^z$ is the element of weighted matrix, and it is the risk connectedness from industry $i$ to $j$.

3.2.2. Network topological features

(1) Network concentration

Concentration is also an important indicator of network structure and represents the density of the linkages. Following Fang et al. (2019), we apply the Herfindahl-Hirschman Index (HHI) that is generally used to measure the extent of concentration in an industry. HHI index equals the sum of the square of market share of each financial institution, and can be used to measure the degree of monopoly. Thereby, the HHI index can reflect the degree of risk network concentration, which is consistent with our definition. It is calculated by:

\begin{equation}
\text{HHI}_s = \sum_{i=1}^{N} \left(\frac{LC_{i,s}}{TLN_s}\right)^2 = \sum_{i=1}^{N} RL_{i,s}^2 \tag{8}
\end{equation}

where $LC_{i,s}$ is the number of edges connected for the node $i$ at window $s$, $TLN_s$ is the total number of network edges, and $RL_{i,s}$ denotes the proportion of connected edges of node $i$ to $TLN_s$ in window $s$, which stand for the degree of node $i$’s relative linkages.

(2) Node strength

The node strength considers not only the number of directly connected edges but also the weights of edges. It can be seen from the adjacency matrix of formula (7) that risk spillover is directional. Therefore, this article pays more attention to the sectors that spread or absorb risks, that is, the out-strength (in-strength) is used to measure the risk contagion (absorption) ability of each sector. Now, we introduce two directional measures of the sector strength, i.e., the out-strength and the in-strength, and these are used to measure each sector’s outgoing and incoming connectedness, respectively. The out-strength (OS) of sector $i$ is the sum of weights $|\beta_{j_i}^z|$ of outgoing edges from sector $i$ to other sectors, as follows:

\begin{equation}
\text{OS}_i = \sum_{j=1}^{N} |\beta_{j_i}^z| \tag{9}
\end{equation}
In-strength (IS) of a sector $i$ is the sum of weights $|D_{ji}|$ of incoming edges from other sectors to sector $i$, as follows:

$$IS_i = \sum_{j=1}^{N} |D_{ji}|$$

(10)

(3) PageRank

Assume that node $i$ has a direct link to node $j$, the more important of node $i$ is, the higher the contribution value of node $j$ is. Thereby, the PageRank reflects the connectedness between one industry and another while considering the influence ability of its neighbors. PageRank algorithm is a variant index of the eigenvector centrality in “adjacency matrix”. As in Wang et al. (2019), we compute the PageRank (PR) indicator through the iterative method which introduces a dynamic process of information spread.

First, we compute the centrality value of sector $i$ based on the risk network matrix (Eq. (7)). And the effect weight is normalizing as follows:

$$E_{ij}^s = \frac{|D_{ij}|}{\sum_{i=1}^{N} |D_{ij}|}$$

(11)

where $E_{ij}^s$ denotes the effect weight by sector $i$ on sector $j$ at window $s$. Second, we adopt the PageRank algorithm proposed by Page et al. (1999) to get PageRank:

$$PR_i^s = \frac{(1 - d)}{N} + d \sum_{j=1}^{N} E_{ij}^s PR_j^s$$

(12)

where $d$ is a damping factor (generally set to 0.85), $PR_i^s$ is the PageRank of sector $i$ and its value always positive. A higher $PR_i^s$ value means that sector $i$ has a greater contribution to systemic risks of network.

3.2.3. Block model

The block model is the main method for spatial cluster analysis of the complex financial networks. It is first proposed by White et al. (1976), which is a method of studying network location modules and is to view social life as an interconnected system of roles. Later, scholars conducted in-depth research and promotion of this concept from many aspects. In addition, many scholars also use the “block model” to study some specific issues, such as the study of the scientific community (Breiger, 1976), the world economy (Snyder and Kick, 1979), the organizational issues and the regional contagion effects (Shen et al., 2019). In short, the concept and the method of the block model have been widely used.

Therefore, the block model could identify the aggregation characteristics among individuals to divide the network into location blocks. Actually, this method not only determines the members included in each block, but also analyzes the role played by each block in the risk propagation process, and explores the risk spatial propagation path (Li et al., 2014; Zhang et al., 2020). There are four role blocks: (i) main benefit, members of this block receive links not only from external members but also from their own members, and the proportion of internal relations is large, while the proportion of external relations is small. In extreme cases, it is called isolated block, that is, the block has no connection with outside. (ii) main spillover, members of this block send more links to other blocks, but send less links to inside members, and receive less links from external. (iii) bilateral spillover, its members send more links to their own members and other blocks’ members, but receive very few external links from other blocks. (iv) brokers, its members both send and receive external relationships, while there are fewer connections between their internal members.

Motivated by Wasserman and Faust (1994), we analyze the relationship of each member from block $B_k$ by the evaluation indicators shown in Table 3. There are $g_k$ nodes in block $B_k$, then the number of possible relationships inside $B_k$ is $n_k(n_k - 1)$. The entire network contains $N$ nodes, so all possible relationships among members in $B_k$ are $n_k(N - 1)$. In this way, we expect the total relationships expectation ratio of the block to be $n_k(n_k - 1)/n_k(N - 1) = (n_k - 1)/(N - 1)$.

4. Empirical results

4.1. Preliminary analysis

In this part, we apply sliding windows to estimate time-varying VaR, CoVaR and construct dynamic evolution tail risk network. We use linear or non-linear quantile regression model to estimate VaR and CoVaR at the quantile level $\tau = 0.05$, and the sliding

| Table 3 |
|---------------------------------|
| **Four types of blocks.**       |
|---------------------------------|
| Internal linkages ratio         | Received linkages ratio         |
| $\leq 0$                        | $>0$                           |
| $\geq (n_k - 1)/(N - 1)$        | bilateral spillover             |
| $<(n_k - 1)/(N - 1)$            | main spillover                  |
| $\leq 0$                        | main benefit                   |
|                                | brokers                        |
window size is set to be \( w = 50 \) trading weeks (corresponds to one year’s weekly data). Though the way, we get whole period \( W = 563 \). To obtain the preliminary analysis about the whole sample dataset, we present the log returns and CoVaR of 24 sectors, and the dynamic evolution about the total connectedness and average lambda of tail risk network from 2008 to 01-04 to 2018–12-31 (window size \( w = 50, W = 563 \)). We also set the quantile level at 0.01 and analyze the network topology. We will provide data analysis upon request.

From Fig. 1, we can find that Chinese stock market (dash-dot line) is characterized by two sharp decline trend periods in early 2008 and mid-2015. At the same time, the market returns and CoVaR fluctuated drastically during 2008 and 2015 market crashes, and both reached the minimum value on these phases. The green fork line of Fig. 1 (bottom) is the estimated penalization parameter (\( \lambda \)) value in the CoVaR estimations. Härdle et al. (2016) think that the average \( \lambda \) stands for the variation of the systemic risk. The purple solid line of Fig. 1 (bottom) shows the dynamic evolution of the total connectedness of the tail risk network. We observe that the \( \lambda \) value appeared twice obvious peaks, corresponding to the US subprime mortgage crisis in 2008 and the domestic stock market turmoil in 2015. However, the total connectedness of tail risk network had at least five peaks, corresponding to the US subprime mortgage crisis in 2008, the European debt crisis in 2011, the money shortage in 2013, the stock market turmoil in 2015 and the trade friction between US and China in 2018. This phenomenon reflects that the total connectedness of tail risk network is more sensitive to the shock of Chinese stock market, and may be an alarm before the market turmoil.

4.2. Network topology characteristics

In this section we first measure the network edge concentration to reflect the overall connectivity of Chinese sectoral tail risk network, and investigate the impact of network edge concentration on systemic risk at the global level. Fig. 2 shows the dynamic evolution trend of the sectoral tail risk spillover network edge concentration. From Fig. 2 we can see that the sectoral tail risk network
edge concentration (HHI) has apparent periodic variation characteristics. This finding is basically consistent with the periodic evolution of systemic risk in the time dimension. Further, the first and last peaks are most notable, which correspond to the 2008 financial crisis and the 2015 domestic stock market turbulence. Now, we take the period (2015/1/30–2016/12/30) of the last peak as an example. In this period, the most significant change of the HHI value is a rapid climb from 0.187 (May 2015) to 0.228 (July 2015). As the potential risks continue to accumulate, the concentration of edges reaches a maximum of 0.232 (January 2016). In the early stage, the Chinese government issued a series of economic reform measures, which stimulated investors’ blind optimistic expectations. Besides, large-scale funds of financial institutions entered the stock market through the way of “highly leveraged” off-market allocation, and the excessive risk-taking behavior of different types of firms in the stock market has led to an increase in indirect correlation. Gradually, due to the downward pressure of China’s macro economy and the strict investigation of off-market allocation by the China Securities Regulatory Commission, a large-scale withdrawal of credit funds and an avalanche-like chain reaction led to the 2015–2016 stock market crash. This shows that as the market turbulence intensifies, the concentration of the risk network will increase, and the edges of the entire network are mostly concentrated in a few highly centralized sectors. At this time, the stability of the network structure is very poor. If these nodes encounter a risk shock or infection, the systemic risk will quickly spread throughout the network, and the risk spillover effect between sectors will be significantly strengthened. Conversely, as the risk is released, the market gradually stabilizes or rises, and the HHI indicator value will become smaller. This phenomenon indicates that the tail risk network exhibits the characteristics of multi-centers rather than a central node. The multi-center network structure facilitates the dispersal of risk information through multiple channels and is conducive to maintaining the stability of the stock market network.

Next, we study the influence of network concentration on systemic risk at global risk network level. The response variable CoVaR is the systemic risk of sector i, and the risk network concentration (HHI) is the source of shock. Here, we adopt orthogonal pulse function to test the short-term dynamic relationship between network edges concentration and systemic risk. This method is widely used to analyze the relationships between variables (Pradhan, 2015; Berument and Froyen, 2009). The pulse function not only presents the direction of the influence, but reflects significance level and time lags. Fig. 3 depicts the response of systemic risk to network edges concentration. In Fig. 3, the vertical axis denotes the systemic risk for the same sector, while the horizontal axis denotes the time lag after the shock in the sample sectors for that month. It is observed that the HHI of edges initially has no significant positive effect on systemic risk. With the accumulation of risks, HHI begins to shows a positive effect on systemic risk from

![Fig. 2. Dynamic evolution of HHI values in tail risk network for Chinese 24 sectors.](image)

![Fig. 3. Response of systemic risk to network interconnection (HHI).](image)
the second month, and reaches the maximum in the fourth month. Gradually, variable HHI disappears to meaningless after nine months. The result shows that HHI has a significant positive impact on systemic risk, but the impact shows a certain lagging feature. The reasonable explanation for this phenomenon is that as the HHI value increases, the connected edges in the network are more controlled on a few central nodes. So, the systemic risks of the network are cumulatively amplified. However, the characteristics of systemic risk “slow accumulation and rapid release” and the shortcomings of Chinese financial market under severe macro-regulation are important reasons for the lagging effect. Of course, it provides strong evidence supporting the results in Fig. 1, which proposes that the concentration of the risk network is more sensitive to the cumulative systemic risks.

In addition to analyzing the overall connectedness of the tail risk network, we also analyze the weighted and directed edges of individual industry nodes. Fig. 4 and Fig. 5 reflect the dynamic evolution of the risk propagation and risk absorption of each sector during the entire period, respectively. First of all, we can see that both the ability of risk propagation or risk absorption of each sector change over time. Many in-strength values are less than one, and only a few sectors have larger values (see Fig. 4), suggesting that these few sectors are seriously infected by external shocks and receive the highest tail risk. In the first shock event period (2008/1/25–2009/12/31), four sectors, i.e., Business and professional services (BPS), Media (MED), Home and personal items (HPI), Healthcare equipment and services (HES) have the largest in-strength values and are the top receivers of tail risk. The results show that the systemic risk from US subprime mortgage crisis has seriously shocked China’s real economy sectors, and these industries have...
accumulated more tail risks. In the second extreme event period (2010/1/29–2012/12/28) that covers the European sovereign debt crisis, the Healthcare equipment and services (HES), Software and service index (SS) and Semiconductor and semiconductor production equipment (SSPE) receive the largest incoming links. During the “Chinese stock market market turbulence” period (2015/1/30–2016/12/30), the strong incoming links come from Business and professional services (BPS), Media (med), Software and service index (SS) and Semiconductor and semiconductor production equipment (SSPE). In the “trade friction between US and China” period (2017/1/26–2018/12/28), five sectors, i.e., Software and service index (SS), Semiconductor and semiconductor production equipment (SSPE), Insurance (INS), Utilities (UT) and Business and professional services (BPS) have the strong incoming links, showing that these sectors are the most affected by tail risk. This finding supports the evidence that in 2018, the US imposes trade sanctions on various industries’ commodities in China, including: communications, electronics, machinery and equipment, automobiles, furniture and so on, which corresponds to the above-mentioned industry classification. Hence, the greater the in-strength value, the deeper the bad impact of a sector by other sectors, and more serious of the damage.

As can be seen from Fig. 5, the distribution of the out-strength differs from that of the in-strength and is relatively even. For example, many sectors have the lower out-strength value, and only a few out-strength values are larger 4, indicating that the few sectors emit the highest systemic risk. In the first event period (2008/1/25–2009/12/31), the strong connected sectors with outgoing links are Energy (ENE), Diversified finance (DF), Insurance (INS), and Utilities (UT). It indicates that affected by the US subprime mortgage crisis, these industries are the main senders of tail risk. In the third event period (2013/1/25–2014/12/31), which covers the money shortage in 2013, the Home and personal items (HPI), Media (MED), and Diversified finance (DF) send the largest outgoing links to others. One of the reasons for the sector of Home and personal items with a high level of outgoing links is that the reduction of currency circulation in the market directly reduces the daily consumption level of consumers. In the fourth event period (2015/1/30–2016/12/30) which covers the “2015–2016 China stock market turbulence”, two financial sectors including Bank (BANK) and Diversified finance (DF), and Media (MED) have strong outgoing links and are involved in most risk spillovers. This phenomenon proves that financial institutions (especially security sector) trigger the recent bear market. Overall, the greater the value of the out-strength, the stronger the ability of one sector to spread the tail risk to other sectors, and the greater the impact on others.

Connectedness alone cannot stand for the systemic importance of an individual sector. We thus calculate the PageRank index since it considers both the interconnectedness and the influence ability of neighbor nodes. To achieve a comprehensive knowledge of the systemic importance for each sector, we draw the heatmap of PageRank value which is shown in Fig. 6. Obviously, the influence of different industries in different periods varies greatly. From Fig. 6, we observe that the PageRank value of most industries is less than 0.05, while only a few sectors have high HHI, showing that these sectors could act as influential sector in Chinese stock market. For example, in first risk event period, the top three sectors are Utilities (UT), Diversified finance (DF) and Media (MED), which are thus systemically important. And Utilities (UT) and Insurance (INS) are the systemically important sectors in second risk event period. The most important reason why UT becomes a systemically important industry is that the utility industry provides infrastructure protection for the development of other industries. Furthermore, in third risk event period the Home and personal items (HPI) and Diversified finance (DF) have larger PageRank value and are thus the largest tail risk contributors during that period. In fourth risk event period only Diversified finance (DF) consistently presents higher PageRank value. One of the major reason for diversified finance being the influential sector is that large-scale abnormal securities margin transactions have caused a surge in systemic risk under unregulated conditions, which in turn affects many associated industries due to asset-liability relationships or high leverage. At the end of 2017, Utilities (UT) and Energy (ENE) are systemically important sectors. As mentioned above, the utilities and financial sectors should be received more attention in the overall time period from both regulators and investors as they become systemically important.

![Fig. 6. Heat map of the PageRank value of each sector for dynamic tail risk network. Notes: the horizontal axis (X) denotes time windows, and the vertical axis (Y) denotes the abbreviation code of sectors (the corresponding full name of each code is presented in Appendix Table A1).](image-url)
important sectors in many risk event periods. Therefore, in the near future, the dependence of utilities industry not reduce significantly, which may reinforce the utilities stocks. Besides, for financial sectors, the development of the whole industry depends much on balancing financial structure, strengthening financial regulation and improving financial innovation. The most fundamental reason is that the financial sector is an important sector in the national economy. It has the characteristics of high industry linkage and strong driving ability. It provides financial support for the development of enterprises in many sectors. Once the financial industry is in a downturn, it will affect the development of the entire industry chain.

4.3. Analysis of block model

This section divided 24 sectors into different blocks through block model, and find out which sectors are likely to cluster in the same community, and then further to examine the relative roles of each block in the sectoral tail risk network. This method can more simply and clearly reflect the function of various industries and risk propagation paths in the risk spillover process. And it is more conducive for the regulatory authorities and investors to grasp risks transmission mechanism, formulate risk prevention measures and optimize asset allocation strategies. Here, we conduct a segmented sample study which covers five sub-samples: period 1 is US subprime crisis from 2008 to 2009; period 2 is European debt crisis from 2010 to 2012; period 3 is money shortage period from 2013 to 2014; period 4 is 2015–2016 Chinese stock market turbulence; period 5 is trade friction between US and China from 2017 to 2018.

According to existing research practices (Chen and Zhao, 2019; Zhang et al., 2020), we used the Ucinet software to divide the block position of the tail risk network adjacency matrix. And, in this process we choose maximum separation depth is 2 and the convergence criterion is 0.2. Therefore, we get four risk spillover blocks in five sub-samples. Table 4 presents the spatial connectedness and role analysis between risk blocks of sectors in five sub-samples.

### Table 4
Spatial connectedness and role analysis between risk blocks of sectors in five sub-samples.

| Blocks | Receiving relationship | Number of members | Expected internal relation ratio (%) | Actual internal relation ratio (%) | Receive links from outside | Emit links to outside | Feature |
|--------|------------------------|-------------------|-------------------------------------|-----------------------------------|---------------------------|----------------------|---------|
|        | first second third four |                   |                                     |                                   |                           |                      |         |
| Sub-period 1 (2008–2009) |
| first  | 1 3 1 4 4 13.04 38.46 19 8  main benefit |
| second | 7 9 2 4 4 13.04 40.91 12 13  bilateral spillover |
| third  | 3 7 23 12 7 26.09 51.11 16 22  bilateral spillover |
| fourth | 9 2 13 32 9 34.78 57.14 20 24  bilateral spillover |
| Sub-period 2 (2010–2012) |
| first  | 10 9 14 6 10 39.13 25.64 54 29  broker |
| second | 6 2 1 1 5 17.39 20.00 27 8  main benefit |
| third  | 32 5 10 2 5 17.39 20.41 24 39  bilateral spillover |
| fourth | 16 13 9 6 4 13.04 13.64 9 38  main spillover |
| Sub-period 3 (2013–2014) |
| first  | 3 3 0 5 6 21.74 27.27 26 8  main benefit |
| second | 15 10 5 6 5 17.39 27.78 15 26  main spillover |
| third  | 32 5 10 2 5 17.39 23.08 21 11  main benefit |
| fourth | 8 8 16 29 8 30.43 47.54 15 32  bilateral spillover |
| Sub-period 4 (2015–2016) |
| first  | 8 6 5 2 7 26.09 38.10 30 13  main benefit |
| second | 22 21 20 5 6 21.74 30.88 9 47  main spillover |
| third  | 2 1 5 4 7 26.09 41.67 36 7  main benefit |
| fourth | 6 2 11 6 4 13.04 24.00 11 19  bilateral spillover |
| Sub-period 5 (2017–2018) |
| first  | 16 12 10 8 7 26.09 34.78 17 30  bilateral spillover |
| second | 3 0 0 1 4 13.04 0 24 4  net benefit |
| third  | 4 6 3 7 7 26.09 15 30 17  broker |
| fourth | 10 6 20 9 6 21.74 20 16 36  main spillover |

Notes: In the left side of Table 4, the diagonal elements present internal relations of each block; the sum of each column (except for diagonal elements) indicates the external relations received from other blocks. Besides, this table also shows the number of members of each block, and the block features.

4.3. Analysis of block model

This section divided 24 sectors into different blocks through block model, and find out which sectors are likely to cluster in the same community, and then further to examine the relative roles of each block in the sectoral tail risk network. This method can more simply and clearly reflect the function of various industries and risk propagation paths in the risk spillover process. And it is more conducive for the regulatory authorities and investors to grasp risks transmission mechanism, formulate risk prevention measures and optimize asset allocation strategies. Here, we conduct a segmented sample study which covers five sub-samples: period 1 is US subprime crisis from 2008 to 2009; period 2 is European debt crisis from 2010 to 2012; period 3 is money shortage period from 2013 to 2014; period 4 is 2015–2016 Chinese stock market turbulence; period 5 is trade friction between US and China from 2017 to 2018.

According to existing research practices (Chen and Zhao, 2019; Zhang et al., 2020), we used the Ucinet software to divide the block position of the tail risk network adjacency matrix. And, in this process we choose maximum separation depth is 2 and the convergence criterion is 0.2. Therefore, we get four risk spillover blocks in five sub-samples. Table 4 presents the spatial connectedness and role analysis between risk blocks of sectors in five sub-samples. From Table 4, it is observed that there are significant differences in the roles played by the four major blocks and the features of different blocks vary across time. Now we take the period 1 and period 5 as examples to analyze risk spatial linkages of 24 sectors. Specifically, in the period 1 and 5, the internal linkages
between the four blocks are 69 and 28, respectively, while the cross-linkages between four blocks are 67 and 88, respectively. It indicates that the spatial spillovers between four blocks are very obvious. In period 1, the number of sending relations in first block is 13, of which there are 5 relations within the block, and the receiving relations from other blocks are 19; the expected internal relation ratio is 13.04%, and the actual relation ratio is 38.46%, so it is called “main benefit block”. Members of first block are ENE, UT, BANK and RE, indicating that the tail risk spillovers between these sectors are closely linked and they are easily affected by the external risk shocks. Furthermore, the number of sending relations in second block is 22, of which there are 9 relations within the block, and the receiving relations from other blocks are 12; the expected internal relation ratio is 13.04%, and the actual relation ratio is 40.91%, so it is called “bilateral spillover block”. Similarly, the third and fourth block are all “bilateral spillover block”. Members of the second block are TSP, CS, DF and INS, showing that if fluctuations generated by these sectors, there will be great subsequent fluctuations to other sectors. E.g., the transportation industry (TSP) is an upstream industry for many industries, and when risks occur, the risks are transferred to other industries through sector linkages. Overall, the internal links ratio of the first and second blocks is low, while the ratio of the third and fourth blocks is high and the third-fourth block emit more links with each other.

In period 5, the number of sending relations in first block is 46, of which there are 16 relations within the block, and the receiving relations from other blocks are 17, including 10 links from fourth blocks; the expected internal relation ratio is 26.09%, and the actual relation ratio is 34.78%, thereby it is called “bilateral spillover block”. The sending links in second block is 4, and the internal links of this block is 0, while only 1 link send to fourth block; so the actual relation ratio of second block is 0% and it is called “net benefit block”. Members of second block are RE, BANK, TSP, MAT and THE, indicating that these industries are more sensitive to external risk shocks and are the largest systemic risk contributors during the US-China trade friction period. Such as, the most possibility reason for the real estate industry (RE) to act as the risk transmitter in the risk network is that, it has a high degree of industry connectivity, which drives the development of materials, manufacturing, bank, home and personal items and other industries. Once the real estate industry is sluggish, it will cause turmoil in the entire industry chain. The sending links of third block is 20, of which 3 links are in this block, and it mainly accepts the relationship from the fourth block; the expected internal relation ratio is 26.09%, and the actual relation ratio is 15%, thereby it is called “broker block”, which plays a role as a “bridge” in systemic risk transmission. Importantly, strong spillover transmission between blocks may depend on the functions of “broker block”. The reason may be that mutual linkage and bidirectional economic or financial effects between their members and other blocks’ members. The sending links of the fourth block is 45, of which 9 internal links of this block, and it mainly sends the relationship to third block; the expected internal relation ratio is 21.74%, and the actual relation ratio is 20%, thereby it is called “main spillover block”. Members of fourth block are BPS, DCGC, DF, INS, SS and SSPE, which are levied high tariffs by the US, therefore they become the spillover engine. Overall, the internal links ratio of the first block is high, while the ratio of the second and third blocks is low. The detailed analysis of period 2-4 are not listed due to space limitations, and the detailed results are shown in Table 4.

In order to more clearly reveal the spillover distribution and relative roles of the tail risk relationship between the 24 sectors, we calculate the density matrix and image matrix of each block (shown in Table 5). The overall density values of the tail risk network in five periods are 0.246, 0.257, 0.219, 0.230 and 0.210, respectively. Here, the overall network density is selected as the critical value. If a block’s density is greater than the overall network density, the corresponding position in the image matrix is assigned 1, otherwise, the value is 0. For example, in period 1, the density of first block is 0.417 that is greater than the overall network density (0.246). It shows that the block’s density is greater than the average value of whole network, and the risk spillover linkages within a block have a significant tendency to concentrate. From the image matrix in Table 5, take period 1 as an example, we find out that: (i)
the diagonal elements of the image matrix in four blocks are 1, showing that internal risk spillovers in the block are closely related and indicating that it has obvious “rich-club” effect; (ii) the first block receives risk spillover connections from the second and fourth blocks; (iii) the second block receives risk spatial connections main from the third block, and it plays the role of a “bridge” and realizes the interconnection of risk spatial spillover in the first and third blocks; (iv) the fourth block realizes the correlation and interaction with other blocks due to the risk spillover association to the first block. The results prove that the interconnections between the different blocks do not occur directly, mainly through the transfer of the first and second blocks.

4.4. Risk spillover transmission mechanism

In the following, we continue to analyze our tail risk spillover across blocks. In this context, Fig. 7 displays the dynamic evolution of the risk spillover transmission mechanism between four blocks. It is observed that the spatial connectedness between the risk spillover blocks is time-varying since the members of the blocks are also time-varying, thereby the blocks’ features in the risk transmission process are different at different periods. From Fig. 7, it is easy to find that the risk transmission path across the blocks is more complicated during the first, second and fifth periods, and the risk transmission path across the blocks is simpler in the third and fourth periods. The most likely reason is that the sources of risk are different, i.e., the first, third and fifth periods are caused by the turmoil in the foreign market, which causes the changes in the relevant industries in the China; the second and fourth periods are caused by domestic macroeconomic regulation or certain sectors with higher levels of accumulation systemic risk. Thus, risk shocks

Fig. 7. Dynamic risk spillover transmission mechanism between four blocks during five periods.
originated in a particular sector spread globally to the sectors of other blocks in a more or less homogeneous way, although some blocks are not directly related to each other. For example, in period 3, the source of infection between the risk spillover blocks is the second block, which spreads systemic risk shock to the first, third and fourth blocks simultaneously. However, there is no significant transmission channel of risk between the first and third blocks. Members of second block are CS, FBT, HES, PBLS and BANK, which should be received more attention and supervision from the regulatory authorities, and investors should avoid investment in these industries. In addition, in period 5, the forth block acts as the risk spillover engine and directly transmits the risk shocks to first, second and third blocks. The members of forth block include BPS, DCGC, DF, INS, SS and SSPE, of which DCGC, SS and SSPE are subject to high tariffs of the trade policy in the US to China, and in this vein, the export of related products in these sectors are seriously affected, which in turn can easy to break out systemic risk. Simultaneously, both the first and third blocks transmit the tail risk from the fourth block to the second block which acts as a distinct bridge and hub. Therefore, the second block is the most sensitive block since it accepts the risk spillover from all blocks. Due to the space limitations, the analysis of risk transmission paths in other periods will not be repeated.

5. Conclusion

This paper applies single-index model in a generalized quantile regression framework to assess non-linearity relationship and variable selection, and in this vein, we construct dynamic tail risk network for 24 Chinese sectors from 2007 to 2018. At the global level, we first analyze the connectedness of systemic risk spillovers in tail risk network, and investigate the impact of network concentration on systemic risk. At the individual sector level, we calculate the risk contagion or absorption intensity of each sector, and adopt PageRank method to identify systemically important sector. Finally, using block model to study the spillover distribution and relative roles of the tail risk relationship between the 24 sectors, and understand the financial risks transmission process across various sectors.

In this research, we report the following findings. First, there is a tail risk network that connects all sectors in Chinese stock market, and it exposes to more systemic risk and total connectedness during market distress. Further, the edge concentration of risk network (HHI) is used to measure risk network interconnectedness and concentration, and it exhibits obvious cyclical features. During the tail event (market downside) periods, the HHI index increases significantly, and then the risk network is relatively single central node structure, thereby, the network stability is poor. The results show that multi-centered financial network, rather than a single pivotal center, can maintain financial market stability. Second, the directional connectedness of sectors shows that systemic risk receivers and transmitters vary across time, and provide an evidence about “Too linked to fail”. Besides, we identify two influential sectors released by utilities and financial sectors, which should be received more attention in the overall time period from both regulators and investors. Finally, we find that the sectoral tail risk network can be divided into four different spillover function blocks by block model, which can more clearly reflect risk spillover distribution and roles of relevant industries in the process of systemic risk transmission. The role of blocks and the spatial spillover transmission path between risk blocks are time-varying.

This study has important policy implications for cross-sector linkages and systemic risk spillovers in Chinese stock market. First, it is necessary for the government to issue favorable policies such as the sectoral development policies or macro-control policies in a timely manner, which will promote the influence of relevant industries in the stock market, and thus create a multi-centered node to maintain the financial market network stability. Second, for investors, they should pay more attention to the systemically important sectors and make reversal strategies around these sectors to configure their assets and portfolios for risk minimization. For supervision department, they may consider the features of four blocks and its spillover paths to formulate different financial regulatory policies that improve the macro-prudential framework during stock market recession and instability periods. A thorough analysis about sectoral tail risk spillover and its spatial connectedness could successfully monitor systematic risks and keep financial system stability, which in turn, contributes to the smooth functioning of the real economy.

Declaration of Competing Interest

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.

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Appendix A. Supplementary data

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