Quantitative Finance

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/rquf20

Multilayer information spillover networks: measuring interconnectedness of financial institutions

Gang-Jin Wang , Shuyue Yi , Chi Xie & H. Eugene Stanley

Quantitative Finance, 2020
https://doi.org/10.1080/14697688.2020.1831047

Multilayer information spillover networks: measuring interconnectedness of financial institutions

GANG-JIN WANG *†¶, SHUYUE YI ‡†¶, CHI XIE † and H. EUGENE STANLEY §

†Business School, Hunan University, Changsha 410082, People's Republic of China
‡School of Management, Fudan University, Shanghai 200433, People's Republic of China
§Department of Physics, Center for Polymer Studies, Boston University, Boston, MA 02215, USA

(*Received 24 January 2020; accepted 25 September 2020; published online 23 October 2020*)

We propose multilayer information spillover networks to measure the interconnectedness of financial institutions by comprehensively considering mean spillover layer, volatility spillover layer and extreme risk spillover layer based on the Granger causality tests in mean, volatility and risk. Using daily returns of 24 Chinese publicly listed financial institutions during 2008–2018, we construct static and dynamic multilayer information spillover networks and analyze different layers' similarity, uniqueness and overlap. Some unique features, which could not be detected in a particular single-layer, are found in multilayer networks. Dynamic topological features of multilayer networks show that significant changes in degrees or unique edges on extreme risk and volatility spillover layers generally occur in the period before a financial stress, e.g. the beginning of the European sovereign debt crisis and 'the 2015–2016 Chinese stock market turbulence,' which can provide early warning signals of the financial stress. The systemically important financial institutions change over time, but banks generally have a high interconnectedness.

Keywords: Financial institutions; Multilayer networks; Information spillover effects; Interconnectedness

JEL Classification: G20, C51, G18

1. Introduction

An important lesson learned from the 2008 global financial crisis is that the traditional micro-prudential supervision focusing on individual risk of financial institutions cannot effectively prevent systemic risk, and so it is necessary to resort to a macro-prudential supervision that considers the financial system as a whole and implements financial regulation in a system context (Yellen 2013). A key reason why traditional micro-prudential supervision (e.g. Basel II) finds it difficult to curb and prevent the formation and spread of systemic risk is that it fails to pay close attention to the interconnectedness among financial institutions and their resulting financial network. Financial institutions form a complex, huge and seemingly sound financial network through business transactions, market positions and other factors. Increasingly tight interconnectedness in the financial system, on the one hand, can bring rapid economic growth and highly dispersed financial risk. But on the other hand, it can lead to the rapid transmission and spread of negative shocks (e.g. the shortfall of jointly held assets) or individual events (e.g. the collapse of Lehman Brothers, a highly interconnected financial institution) in the financial network. This further results in an exponential growth of systemic risk, and ultimately causes financial network collapse and triggers systemic events (e.g. financial crisis). This also introduces a new moral hazard problem posed by 'too interconnected to fail' financial institutions in the post-crisis era. Thus the Financial Stability Board (FSB) uses the interconnectedness of financial institutions as one of the indicators for identifying global systemically important banks.† Accordingly, how to accurately measure the interconnectedness of financial institutions has become a

*Corresponding author. Email: wanggangjin@hnu.edu.cn
¶These authors contributed equally to this work.

† FSB measures the interconnectedness by merely using the aggregated cross border activity, while ignores the centrality of each institution, which is a main indicator in our work.

priority and crucial issue faced by the academia and regulators in quantifying systemic risk and identifying systemically important financial institutions.

Because the financial system is a huge complex interactive system, in recent years scholars have begun to use complex network theory to investigate the interconnectedness of financial institutions (Levy-Carciente *et al.* 2015). For example, Battiston *et al.* (2016) point out that 'Economic policy needs interdisciplinary network analysis and behavioral modeling.' This is because the near collapse of the financial system in the 2008 global financial crisis and its long-term effects on the global economy cannot be explained by traditional economic theory due to the complexity of the financial system. Network theory may provide guidance on better monitoring and management of highly interconnected economic and financial systems and may give aid in anticipating and managing future crises. Although many financial network models have been proposed for measuring the interconnectedness of financial institutions, e.g. mean spillover network (Billio *et al.* 2012), volatility spillover network (Diebold and Yilmaz 2014), and (extreme or tail) risk spillover network (Hautsch *et al.* 2015, Härdle *et al.* 2016, Wang *et al.* 2017), most of them are limited to simply abstracting the financial system into a single-layer network with only a certain type of information or interconnectedness. With a single-layer network it is hard to capture the diversity and heterogeneity of information transmission and its interconnectedness among financial institutions, and thus it is necessary to use multilayer networks, which consider heterogeneous information and the multilayer structure of a complex system, to understand the interaction behavior in the financial system. Multilayer networks, where links on each layer represent different types of connections among the same set of nodes, can combine together different interconnectedness measures to describe complex financial systems effectively. Therefore, from the perspective of information spillovers, we here propose a concept and model of multilayer information spillover networks, including a mean spillover layer, a volatility spillover layer and an extreme risk spillover layer, for investigating the interconnectedness of financial institutions comprehensively.

We apply multilayer information spillover networks to study the connectedness of China's financial institutions. In recent years, China's financial system has developed rapidly, playing an important role in promoting China's economic growth. In the list of global systemically important banks (G-SIBs) delineated by the group of global banking regulators (i.e. Basel Committee on Banking Supervision), Bank of China (BOC) was among them in 2011. Subsequently, Industrial and Commercial Bank of China (ICBC), Agricultural Bank of China (ABC) and China Construction Bank (CCB) were selected as G-SIBs between 2013 and 2015. These four banks are known as the 'Big Four' stated-own commercial banks. Ping An Insurance (Group) Co. of China, Ltd was listed among the first global systemically important insurers (G-SIIs) announced in 2014. Global systemically important financial institutions (G-SIFIs) are critical to the stability of the global financial system, because once one of them goes bankrupt, it will cause great harm to financial markets and the real economy. As China's financial institutions become increasingly influential in the world, accurately measuring the connectedness of China's financial institutions is extraordinarily important for the Chinese financial system but also for global financial stability.

Our proposed multilayer information spillover networks for comprehensively measuring the interconnectedness of financial institutions are based on Granger causality tests in mean, volatility and risk that are unified information spillover testing procedures proposed by Hong (2001) and Hong *et al.* (2009). Using daily returns of 24 Chinese publicly listed financial institutions during the period of 2008–2018, we construct static and dynamic multilayer information spillover networks and employ topological statistics of similarity, uniqueness and overlap to investigate interconnectedness in China's financial system.

In summary, our work has the following contributions. First, our investigation on information spillover effects among Chinese financial institutions from a multilayer network viewpoint constitutes a new idea in information spillover research and provides a new tool to risk management. Second, our proposed multilayer information spillover networks comprehensively consider mean spillover effects, volatility spillover effects and extreme risk spillover effects, which can describe the interconnectedness in a complex financial system more efficiently and also provide a new perspective for studying information spillover effects. To the best of our knowledge, our work is the first attempt to propose a multilayer directed network model for examining the interconnectedness among financial institutions based on information spillover effects. According to Abbassi *et al.* (2017), although the interconnectedness detected by market-based data is not the real correlation between institutions given by the associated balance sheet data that are hardly available, it can reflect supervisory balance sheet information and serve well as a risk monitoring tool. Thus, our proposed multilayer information spillover network model based on market data would enrich systemic risk research in theory, because it provides a new connectedness analytical tool for measuring systemic risk contributions of financial institutions and identifying systemically important financial institutions. Third, our important finding is that in the period before a financial stress, topological features of extreme risk and volatility spillover layers show a foreboding ability by significant changes, and the value of average edge overlap drops significantly, reaching a minimum point. Thus these indicators can be used as early warning signals of financial stress for regulators.

The remaining structure of this paper is organized as follows. In section 2, we review the related literature. In section 3, we introduce the methodologies of constructing multilayer information spillover networks and some topological measurements of multilayer networks. In section 4, we present the empirical data and results. In section 5, we draw our conclusions.

2. Literature review

Our research contributes to the literature on measuring the interconnectedness and systemic risk contribution of financial institutions based on market data, also known as market-based measurements. The market-based measurements can be classified into three types: (i) correlation-based approaches, (ii) portfolio methods, and (iii) network models.

Correlation-based approaches examine the changes in asset return correlations among financial institutions to measure systemic risk, mainly including the correlation coefficient method (Huang *et al.* 2009, Patro *et al.* 2013) and the principal components analysis (Kritzman *et al.* 2011, Billio *et al.* 2012). A limitation of correlation-based approaches is that they can only quantify the overall level of systemic risk and cannot measure systemic risk contribution of financial institutions and the risk spillover degree of one financial institution to another.

Portfolio methods consider the entire financial system as a combination of financial institutions, and evaluate systemic risk contribution of a financial institution by quantifying the tail interconnectedness between individual financial institution and the financial system. Some well-known portfolio methods in the literature include, among others, conditional value-at-risk (CoVaR) (Adrian and Brunnermeier 2016), systemic impact index (SII) and vulnerability index (VI) (Zhou 2010), Shapley value (Tarashev *et al.* 2010), marginal expected shortfall (MES) and systemic expected shortfall (SES) (Acharya *et al.* 2017), component expected shortfall (CES) (Banulescu and Dumitrescu 2015), and SRISK (Brownlees and Engle 2017). Although portfolio methods that consider the direction of risk transmission are widely used to measure the connectedness and systemic risk contribution of financial institutions, they only focus on the institution-to-system or system-to-institution interdependence and fail to capture the network interconnectedness of risk spillover, thus underestimating systemic risk of highly correlated financial institutions (Hautsch *et al.* 2015).

Network models provide a comprehensive consideration of all possible interconnectedness of the financial system. The emergence of network models is mainly attributed to the deepening understanding of scholars on the network topology and systemic risk of the financial system in the post-crisis era. In the framework of information spillover, representative network models include mean spillover network based on the Granger causality in mean (Billio *et al.* 2012), volatility spillover network using the variance decompositions (Diebold and Yilmaz 2014), tail risk spillover network (Hautsch *et al.* 2015), tail-event driven network (TENET) based on CoVaR (Härdle *et al.* 2016), extreme risk spillover network using the Granger causality in risk (Wang *et al.* 2017), and LASSO-CoVaR network (Xu *et al.* 2019).† The above information spillover networks are widely applied in measuring the interconnectedness and systemic risk of financial institutions (Hautsch *et al.* 2014, Betz *et al.* 2016, Diebold and Yilmaz 2015, Huang *et al.* 2016, Wang *et al.* 2018a, 2018b, Demirer *et al.* 2018, Fang *et al.* 2018), but the existing research is based on a single type of information spillover network, which cannot fully capture all possible interconnectedness among financial institutions.

Because a complex system (e.g. financial system) is composed of many network layers with different structure and functions, multilayer networks become a novel analytic tool for studying the interconnectedness and interactive behavior among a large number of agents in a complex system (Buldyrev *et al.* 2010, Domenico *et al.* 2013, Boccaletti *et al.* 2014, Kivelä *et al.* 2014). Multilayer networks are also applied to map the financial system. For example, Langfield *et al.* (2014) construct multilayer UK interbank networks, including interbank exposures layer and interbank funding layer. Bargigli *et al.* (2015) use a unique dataset of interbank transactions based on supervisory reports of Italian banks to the Central Bank of Italy and build multilayer Italian Interbank networks. Poledna *et al.* (2015) establish multilayer networks of the Mexican banking system with four layers, including networks of exposures from derivatives, security cross-holdings, foreign exchange exposures, and deposits & loans. Molina-Borboa *et al.* (2015) also investigate the Mexican banking system using multilayer exposures networks. Aldasoro and Alves (2018) examine multilayer interbank networks of the European banking system using the bilateral exposures database among 53 large European banks. Li and Wen (2017) study multilayer networks of China's guarantee market with three layers corresponding to different types of guarantee relations. The above studies show that layers have different topological features and a certain single-layer network cannot be represented or replaced by other layer networks. Especially, Poledna *et al.* (2015) point out that measuring systemic risk by a single-layer network will underestimate the total systemic risk; and Aldasoro and Alves (2018) find that banks have different systemic importance at different layers, so focusing on a single-layer is misleading. Therefore, modeling multilayer networks will help us comprehensively understand and describe the complex heterogeneous interactions in the financial system.

Note that the above multilayer networks for measuring interconnectedness of financial institutions are almost based on interbank asset and liability exposures. However, such credit and liquidity exposures data of financial institutions are business confidential and not publicly available. Thus we resort to publicly disclosed market data and propose the model of multilayer networks from the information spillover perspective.‡ Our work is closely related to the research of Musmeci *et al.* (2017) who construct multilayer interdependence

† In the existing literature, there are also some other econometrics-based network models including Bayesian graphical VAR network (Ahelegbey *et al.* 2016), Bayesian sparsity VAR network based on a parametric measure (Ahelegbey *et al.* 2016) and a nonparametric approach (Billio *et al.* 2019c), time-varying systemic risk network using Markov switching graphical SUR models (Bianchi *et al.* 2019), and latent position estimation network (Hoff *et al.* 2002).

‡ Note that there is a stream of research that studies multilayer networks based on market data by econometric measures. For example, Hoff (2015) develops the multilinear tensor regression model and introduces multilayer networks of international relations. Lacasa *et al.* (2015) use the horizontal visibility graph algorithm to map multidimensional time series into indirected multilayer networks that can quantify periods of financial instability. Billio *et al.* (2019a) propose multilayer temporal networks by a zero-inflated logit regression for examining the interconnectedness among European financial institutions. Billio *et al.* (2019b) introduce a new dynamic linear model for tensor-valued response variables and covariates and provide an original study of time-varying economic and financial multilayer networks. Casarin *et al.* (2020) propose multilayer networks of oil market through a novel Bayesian graphical vector autoregressive model.

networks with four layers corresponding to linear, nonlinear, tail, and partial correlations among stock returns. Our proposed multilayer information spillover networks differ from multilayer interdependence networks in that (i) our multilayer networks are directed networks representing the information spillover effect from one institution to another, while multilayer interdependence networks are undirected networks, (ii) our multilayer networks are based on the Granger causality tests with a unified framework, while multilayer interdependence networks are built on four different dependence measurements, and (iii) multilayer interdependence networks are filtered by the planar maximally filtered graph (PMFG) procedure (Tumminello *et al.* 2005), while our multilayer networks are built by the Granger causality tests in mean, volatility and risk.

To study the interconnectedness evolution among financial institutions, we construct dynamic multilayer information spillover networks. Our dynamic networks are different from some previous dynamic and temporal networks (Kostakos 2009, Kolar *et al.* 2010, Holme and Saramäki 2012, Gallotti and Barthelemy 2015). For example, Kostakos (2009) introduces temporal graphs, which describe events over periods of time to remain the original time-varying information. Holme and Saramäki (2012) review the emergent field of temporal networks and illustrate the benefit from the temporal network approach. Gallotti and Barthelemy (2015) design multilayer temporal networks of public transport by collecting directly the route information between two nodes at a given moment measured in minutes. In summary, the dynamic and temporal networks designed in the above literature are observed directly, while the information spillover effects cannot be directly observed and thus our dynamic multilayer information spillover networks need to be calculated by a interval of time series. However, all of the dynamic or temporal networks can estimate and describe the real structure better than static networks, even though they are constructed by different methods.

3. Methodology

Our proposed multilayer information spillover networks including mean spillover layer, volatility spillover layer and extreme risk spillover layer are based on the Granger causality tests in mean, volatility and risk of Hong (2001) and Hong *et al.* (2009). In this section, we firstly introduce how to examine information spillover effects between financial institutions. We then construct multilayer information spillover networks and finally describe some measurements of multilayer networks to investigate the interconnectedness of financial institutions.

3.1. Information spillover effect test

When measuring the information spillover effects or interconnectedness among financial institutions, we usually consider the mean spillover effect that generally refers to the impact of price changes or returns in one institution on others and the volatility spillover effect that reflects the effect of the price fluctuations of one institution on others. Although volatility is commonly used to quantify risk, it can only properly measure small risks in practice and cannot capture extreme risk when large adverse market movements or tail events occur (Hong *et al.* 2009). Moreover, the violent price fluctuations or large losses of one highly interconnected institution will often spread its financial risks to other institutions, resulting in the instability of the financial system. Therefore, it is necessary to introduce value-at-risk (VaR) to estimate extreme or tail risk and examine the extreme risk spillover effect for capturing large losses, or large adverse market movements.

We adopt the sample cross-correlation function (CCF)-based Granger causality test to estimate information spillover effects including mean spillover effect, volatility spillover effect and extreme risk spillover effect between two financial institutions, proposed by Hong (2001) and Hong *et al.* (2009). The mean (volatility) spillover effect captures whether the change (volatility) in price of a financial institution will lead to the change (volatility) in prices of other institutions, which is the first (second) order moment process. The extreme risk spillover effect is to measure the extreme downside risk movements, which corresponds to the tail risk spillover effect in high-order moments (e.g. skewness and kurtosis).

Let $\{r_{1,t}\}$ and $\{r_{2,t}\}$ denote the return series of financial institutions 1 and 2. Consider information set $\{I_{t-1}\} = \{I_{1,t-1}, I_{2,t-1}\}$, where $I_{1,t-1} = \{r_{1,t-1}, \ldots, r_{1,1}\}$ and $I_{2,t-1} = \{r_{2,t-1}, \ldots, r_{2,1}\}$ are the information sets available at time $t-1$ for financial institutions 1 and 2, respectively. To test for mean spillover effect, volatility spillover effect, and extreme risk spillover effect from financial institution 2 to financial institution 1, we, respectively, consider the following three pairs of null and alternative hypotheses:

$$\begin{cases} \mathrm{H}_0 : E\left(r_{1,t} \mid I_{1,t-1}\right) = E\left(r_{1,t} \mid I_{t-1}\right) \\ \mathrm{H}_A : E\left(r_{1,t} \mid I_{1,t-1}\right) \neq E\left(r_{1,t} \mid I_{t-1}\right) \end{cases}, \tag{1}$$

$$\begin{cases} \mathrm{H}_0 : E\left\{\mathrm{Var}\left(r_{1,t} \mid I_{1,t-1}\right) \mid I_{1,t-1}\right\} = \mathrm{Var}\left(r_{1,t} \mid I_{t-1}\right) \\ \mathrm{H}_A : E\left\{\mathrm{Var}\left(r_{1,t} \mid I_{1,t-1}\right) \mid I_{1,t-1}\right\} \neq \mathrm{Var}\left(r_{1,t} \mid I_{t-1}\right) \end{cases}, \tag{2}$$

$$\begin{cases} \mathrm{H}_0 : P\left(r_{1,t} < -V_{1,t} \mid I_{1,t-1}\right) = P\left(r_{1,t} < -V_{1,t} \mid I_{t-1}\right) \\ \mathrm{H}_A : P\left(r_{1,t} < -V_{1,t} \mid I_{1,t-1}\right) \neq P\left(r_{1,t} < -V_{1,t} \mid I_{t-1}\right) \end{cases}, \tag{3}$$

where $V_{1,t}$ is the corresponding downside VaR of financial institution 1 at time t. Following Hong *et al.* (2009), we define the risk indicator $Z_{i,t} = \mathbf{1}(r_{i,t} < -V_{i,t})$, $i = 1, 2$, where $\mathbf{1}(\cdot)$ is the indicator function. When the condition is met, the risk indicator $Z_{i,t}$ takes the value of 1, otherwise it takes 0. Thus, the null and alternative hypotheses of testing for extreme risk spillover effect in equation (3) can be equivalently stated as follows:

$$\begin{cases} \mathrm{H}_0 : E\left(Z_{1,i} \mid I_{1,t-1}\right) = E\left(Z_{1,t} \mid I_{t-1}\right) \\ \mathrm{H}_A : E\left(Z_{1,i} \mid I_{1,t-1}\right) \neq E\left(Z_{1,t} \mid I_{t-1}\right) \end{cases}. \tag{4}$$

Based on the three pairs of null and alternative hypotheses, we employ the CCF-based Granger causality test to measure information spillover effects. The CCF-based Granger causality test includes two steps. The first step selects the appropriate model, e.g. the ARMA-GARCH model as in Hong (2001), to fit return series of financial institution i and obtain the estimations of the residuals $\hat{\varepsilon}_{i,t}$ and the conditional variances $\hat{h}_{i,t}$.

The mean spillover effect is directly tested against the standardized residuals $\hat{u}_{i,t}$ (see, equation (5)). The volatility spillover effect is tested against the centered squared standard residuals (see equation (6)). To test the extreme risk spillover effect, we follow Hong *et al.* (2009) and firstly estimate VaR series $\hat{V}_{i,t}$ of financial institution i through the standardized residuals and the conditional variances (see equation (7)) and then obtain the risk indicator $\hat{Z}_{i,t}$ (see equation (8)). Therefore, as in Liu *et al.* (2008) and Li *et al.* (2011), we measure information spillover effects between financial institutions in a unified econometrics framework by estimating the Granger causality tests in mean, volatility and risk based on the ARMA-GARCH model. Mathematically, we have

$$\hat{u}_{i,t} = \hat{\varepsilon}_{i,t}/\sqrt{\hat{h}_{i,t}}, \tag{5}$$

$$\hat{v}_{i,t} = \hat{\varepsilon}^2_{i,t}/\hat{h}_{i,t} - 1, \tag{6}$$

$$\hat{V}_{i,t} = -\hat{\mu}_{i,t} - z_\alpha\sqrt{\hat{h}_{i,t}}, \tag{7}$$

$$\hat{Z}_{i,t} = \mathbf{1}(r_{i,t} < -\hat{V}_{i,t}), \tag{8}$$

where z_α is the left α-quantile for the standardized residuals.

The second step constructs a statistic Q based on the estimated series in the first step to test whether there is an information spillover effect between pairs of financial institutions. We take the Granger causality test in risk for examining extreme risk spillover effect from institution 2 to institution 1 as an example.

Suppose $\hat{Z}_{1,t}$ and $\hat{Z}_{2,t}$ are two series of estimated risk indictors of financial institutions 1 and 2, the sample cross-correlation function (CCF) is defined by

$$\hat{\rho}(j) = \hat{C}(j)/(\hat{S}_1\hat{S}_2), \quad j = 1, 2, \ldots, T-1, \tag{9}$$

where $\hat{S}_i$ is the sample standard deviation of $\hat{Z}_{i,t}$, T is the sample size, and $\hat{C}(j)$ is the sample cross-covariance function between $\hat{Z}_{1,t}$ and $\hat{Z}_{2,t}$ at positive lag j, which is defined by

$$\hat{C}(j) = T^{-1}\sum_{t=1+j}^{T}(\hat{Z}_{1,t} - \hat{\bar{Z}}_1)(\hat{Z}_{2,t-j} - \hat{\bar{Z}}_2), \quad 0 \le j \le T-1, \tag{10}$$

where $\hat{\bar{Z}}_i = T^{-1}\sum_{t=1}^{T}\hat{Z}_{i,t}$, $i = 1, 2$. Following Hong *et al.* (2009), we construct a statistic Q that contains the weighted average sum of sample CCFs of all lag orders, given by

$$Q = \left\{T\sum_{j=1}^{T-1}\left[k^2(j/M)/\hat{\rho}^2(j) - C_T(M)\right]\right\} / \left(2D_T(M)\right)^{1/2}, \tag{11}$$

where M is an effective lag truncation order, and $k(\cdot)$ is the kernel function.

We follow the suggestion of Hong *et al.* (2009) and use the Daniel kernel function, because it not only takes all lag orders into account, but also considers a decreasing weight with an increasing time lag, which is consistent with the fact that financial markets are more susceptible to recent events than long-term events. Specifically, the Daniel kernel function is defined as

$$k(x) = \sin(\pi x)/(\pi x). \tag{12}$$

In equation (11), $C_T(M)$ and $D_T(M)$ are the centering and standardization constants, respectively, which are expressed as

$$C_T(M) = \sum_{j=1}^{T-1}(1 - j/T)k^2(j/M), \tag{13}$$

$$D_T(M) = \sum_{j=1}^{T-1}(1 - j/T)\{1 - (j+1)/T\}k^4(j/M). \tag{14}$$

If the null hypothesis of the Granger causality in risk is true, i.e.there is no extreme risk spillover effect from institution 2 to institution 1, the statistic Q is convergent to the standard normal distribution. Since Q tends to be positive infinity as T increases, the test value uses the right-hand side of the standard normal distribution. When the estimated value Q is higher than the right-tail critical value of the standard normal distribution at a given significance level β (in our case, $\beta = 0.05$),† it is considered that institution 2 has an extreme risk spillover effect on institution 1. Similarly, when considering the standardized residuals and centralized standard residuals of institutions 1 and 2 in equations (9)–(14), we can obtain mean and volatility spillover effects from institution 2 to institution 1, respectively.

3.2. *Multilayer information spillover network*

We denote the proposed multilayer information spillover networks as $\Omega = \{G^{[1]}, G^{[2]}, \ldots, G^{[L]}\}$ with L layers and N nodes, where $G^{[\alpha]} = G(V, A^{[\alpha]})$ is layer α of multilayer information spillover networks, $V = \{1, 2, \ldots, N\}$ is the set of nodes, and $A^{[\alpha]}$ is the set of edges of layer α. On each layer, nodes represent financial institutions, and a directed edge indicates that there is a corresponding information spillover effect from the starting financial institution to the terminal financial institution. In our case, $L = 3$, and we assume that the first layer, the second layer and the third layer correspond to mean spillover layer, volatility spillover layer and extreme risk spillover layer, respectively. For any two financial institutions $i, j \in V$, we draw a directed edge from i to j on the first (second, third) layer, if institution i has a mean (volatility, extreme risk) spillover effect on institution j. $A^{[\alpha]} = \{a^{[\alpha]}_{ij}\}_{N\times N}$ is a directed

† Note that when performing multiple hypothesis testing, the significance level of each single test should be corrected to avoid a high false positive rate (Tumminello *et al.* 2011). Following Mazzarisi *et al.* (2020), we apply the Bonferroni correction by setting $\beta' = \beta/(N(N-1))$ to prove the robustness of our empirical results. We find that (i) although the number of unique edges on each layer and the number of unique edges of some financial institutions using β' are less than those using β, the trend of unique edges on each layer and that of finical institutions using β' are similar to those using β and (ii) the similarity and overlap measures also have similar results and patterns, confirming that our empirical results are robust. The detailed results based on the Bonferroni correction can be available upon request.

binary connection matrix for all pairs of institutions i and j on layer α, where the element $a_{ij}^{[\alpha]}$ in the matrix $A^{[\alpha]}$ is defined as

$$a_{ij}^{[\alpha]} = \begin{cases} 1, & \text{if } i \neq j \text{ and } i \text{ has a corresponding spillover effect on j on layer } \alpha \\ 0, & \text{else} \end{cases} . \tag{15}$$

Thus, multilayer information spillover networks are simplified to a 3 dimensional $N \times N$ adjacency matrix by mathematical notation. Considering the unpredictability of the financial system and dynamic changes of the interconnectedness among financial institutions, we build time-varying multilayer information spillover networks using rolling window analysis. The sample interval of the investigated daily return series is divided into rolling windows with width w and size step δ, where the width w is the length of the daily return series in each window, and the size step δ is the interval between two continuous windows. Following Wang *et al.* (2017), we select a width w of 240 days and a step size δ of 20 days, corresponding to one trading year and one trading month in the Chinese stock market approximately. Thus, the period for the first window is from the first day to the 240th day of the sample period, the period for the second window is from the 21st day to the 260th day, and so on. Then, we note time-varying multilayer information spillover networks as Ω_t.

3.3. *Multilayer network measures*

3.3.1. Similarity measures. In multilayer information spillover networks, we explore whether there is similarity between different layers. First, we introduce the degree of layer α, which indicates the number of edges on layer α, to character the total interconnectedness of layer α. The greater the degree of a layer, the tighter the interconnectedness among financial institutions on the layer. The degree of layer α is defined as

$$a^{[\alpha]} = \sum_{i,j=1,i\neq j}^{N} a_{ij}^{[\alpha]}, \quad \alpha = 1, 2, \ldots, L, \tag{16}$$

where $a_{ij}^{[\alpha]}$ represents the edge (or the corresponding information spillover effect) from financial institution i to j on layer α, which is defined in equation (15).

We introduce a similarity measurement among different layers from an institutional-level perspective, i.e. the Spearman's correlation coefficient $\rho^{[\alpha,\beta]}$, which is used to explore the similarity of the rankings of financial institutions between layers α and β and is formally defined as:

$$\rho^{[\alpha,\beta]} = 1 - \frac{6\sum_i (R_i^{[\alpha]} - R_i^{[\beta]})^2}{N(N^2-1)}, \quad \alpha, \beta = 1, 2, \ldots, L, \tag{17}$$

where N is the number of financial institutions, and $R_i^{[\alpha]}$ and $R_i^{[\beta]}$ represent the degree rankings of financial institution i on layers α and β, respectively.

3.3.2. Uniqueness measures. To quantify how peculiar the structure of layer α is, we introduce a uniqueness measure $U^{[\alpha]}$ by computing the number of unique edges on layer α, i.e.

$$U^{[\alpha]} = \sum_{i,j=1,i\neq j}^{N} a_{ij}^{[\alpha]} \prod_{\beta=1,\beta\neq\alpha}^{L} (1 - a_{ij}^{[\beta]}), \quad \alpha = 1, 2, \ldots, L, \tag{18}$$

which captures the number of edges that exist only on layer α rather than other layers. $U^{[\alpha]}$ is 0, only if all edges on layer α exist on at least one of the other layers. A larger $U^{[\alpha]}$ represents that layer α has a greater number of unique edges, indicating the peculiarity of layer α, because if layer α is absent, the unique edges on layer α will be ignored, i.e. the corresponding interconnectedness between financial institutions will not be captured.

We also consider unique edges of each institution i on layer α, i.e.

$$U_i^{[\alpha]} = \sum_{j=1,j\neq i}^{N} a_{ij}^{[\alpha]} \prod_{\beta=1,\beta\neq\alpha}^{L} (1 - a_{ij}^{[\beta]}),$$
$$\alpha = 1, 2, \ldots, L,\ i = 1, 2, \ldots, N. \tag{19}$$

3.3.3. Overlap measures. To comprehensively understand the interconnectedness among financial institutions, we use a projection network of multilayer information spillover networks, denoted as $\Pi(V, A)$, by ignoring the fact that the link between two institutions belongs to different layers and drawing an edge from institution i to institution j if institution i has at least one information spillover effect on institution j. $A = \{a_{ij}\}$ is an adjacency matrix for all institutions i and j in the projection network, and its element is defined as

$$a_{ij} = \begin{cases} 1, \exists \alpha, a_{ij}^{[\alpha]} = 1 \\ 0, \text{ else} \end{cases} . \tag{20}$$

We measure the number of edges in the projection network, i.e. the number of edges presenting on at least one layer between institutions, given by

$$K = \sum_{i,j=1,i\neq j}^{N} a_{ij} = \sum_{i,j=1,i\neq j}^{N} \left(1 - \prod_{\alpha=1}^{L} (1 - a_{ij}^{[\alpha]})\right). \tag{21}$$

In multilayer information spillover networks, the same directed edge between institutions may exist on different layers. We introduce a measure of average edge overlap O to quantify how many layers each edge appears on average, which is defined as

$$O = \frac{1}{K} \sum_{i,j=1,i\neq j}^{N} \sum_{\alpha=1}^{L} a_{ij}^{[\alpha]}. \tag{22}$$

Note that the average edge overlap is 1, only when the connections of each layer are completely different, i.e. each edge appears only on one layer of multilayer networks. When all institutions on all layers are connected identically, the average edge overlap is the number of layers. Thus, a greater average edge overlap indicates a higher similarity or homogeneity among layers in multilayer information spillover networks.

To identify relatively important financial institutions, we describe the overlapping degree of institution i, which is the sum of edges on institution i at all layers. If the overlapping degree of a financial institution is high, it indicates that the institution has strong connection with other institutions, so the financial institution is considered to be a central node in multilayer networks. The overlapping degree o_i of financial institution i is defined as

$$o_i = \sum_{\alpha=1}^{L} \sum_{j=1, j \neq i}^{N} a_{ij}^{[\alpha]}, \quad i = 1, 2, \ldots, N. \tag{23}$$

Then, we introduce the participation coefficient to supplement the information on the overlapping degree. The participation coefficient P_i measures the distribution of the nodes at each layer, which is expressed as

$$P_i = \frac{L}{L-1}\left[1 - \sum_{\alpha=1}^{L}\left(\frac{k_i^{[\alpha]}}{o_i}\right)^2\right], \quad i = 1, 2, \ldots, N, \tag{24}$$

where $k_i^{[\alpha]}$ is the degree of node i on the layer α. The participation coefficient of the node is 0, only if the connection between the node and other nodes exists only on one layer, and the nodes on other layers have no connection with other nodes. If the connection of nodes to other nodes is evenly distributed among the layers, the node participation coefficient is 1. The higher the participation coefficient, the more uniform the connection between the nodes and other nodes is distributed in the multilayer network.

4. Data and empirical analysis

4.1. Data set

We apply multilayer information spillover networks to explore the interconnectedness of Chinese financial institutions.† Because a large number of relatively important financial institutions were not listed until 2007 (e.g. China Construction Bank, China CITIC Bank, Bank of Communications, China Life Insurance, and China Ping An Insurance), we select the January 2, 2008 as the starting date for the sample period, and the December 28, 2018 as the ending date. According to a widely used industry taxonomy, i.e. the Global Industry Classification Standard (GICS), we finally select 24 Chinese publicly listed financial institutions in China's A-share market, including 14 banks, 7 securities and 3 insurances, by screening out some financial institutions which had a long time suspension period. We collect daily closing prices of the 24 publicly listed financial institutions in China from the Wind Info. The daily return $r_{i,t}$ of financial institution i is defined as $r_{i,t} = \ln(p_{i,t}/p_{i,t-1}) \times 100$, where $p_{i,t}$ is the daily closing price of financial institution i on day t. There are 2677 observations for each return series. Table 1 lists these 24 financial institutions' details, including the ticker code, full name, the corresponding abbreviation, and descriptive statistics of daily returns.

Table 1 shows that (i) the average return value of securities and insurances is negative, while that of most banks is positive, (ii) the differences in the maximum and minimum returns of all financial institutions are extremely small, and (iii) the maximum loss (i.e. the absolute minimum return) is greater than the maximum return. Securities have the highest volatility in returns, while banks' return volatility is generally the smallest among the three industries. The four large state-owned commercial banks (i.e. BOC, ICBC, CCB and Bank of Communications (BOCOM)) have the least fluctuations, which is consistent with the risk perception of China's financial institutions.

In addition, the Box-Pierce statistics (Box and Pierce 1970) of the returns and squared returns show that the null hypothesis of no serial autocorrelation up to the 10th or 20th orders is rejected, suggesting that the serial autocorrelation and the conditional heteroscedasticity (or volatility clustering) exist in the returns of each financial institution. Thus, we employ the ARMA model and the GARCH model to capture the serial autocorrelation and the conditional heteroscedasticity of the returns, respectively. The Jarque-Bera statistic of each return series shown in table 1 rejects the null hypothesis of normal distribution for the returns. Therefore, the Student's t distribution is used to fit the residual term in the ARMA-GARCH model. Specifically, we apply the ARMA(p,q)-GARCH(r,s)-t model to fit the returns. We adopt the Schwartz information criterion (SIC) to set the lag orders p and q of the mean equation (i.e. the ARMA model). Following Hansen and Lunde (2003) who compare the conditional heteroscedasticity volatility models with different lag orders r and s and find that no other model is more effective than GARCH(1, 1) on the fitting effect, we set GARCH(1, 1) as the variance equation to simplify the parameter selection.‡

4.2. Empirical results

In our empirical analysis, we focus on two types of multilayer information spillover networks: (i) static multilayer information spillover networks with different lag orders (i.e. M) and (ii) time-varying multilayer information spillover networks.

† Some would take issue with the Chinese stock market data due to its market efficiency. Here we would not argue that China's stock market even other national markets (e.g. the USA) are perfect in efficiency at all times, but we should admit that 'it is harder to fool markets than to fool regulators' as Diebold and Yilmaz (2014) said. We also should be optimistic that the Chinese stock market has become fairly efficient after a series of institutional and regulatory reforms (e.g. the non-tradable share reform, the margin-trading and short-selling program, the launch of the Shanghai-Hong Kong Stock Connect, the Shenzhen-Hong Kong Stock Connect and the Shanghai-London Stock Connect, and the inclusion of China's A-shares in the MSCI Emerging Market Index and in the FTSE Emerging Markets Index), which is also supported by the recent literature on the efficiency of China's stock market (see, e.g. Hung 2009, Chong *et al.* 2012, Carpenter *et al.* 2015, Wang *et al.* 2018a, Huang *et al.* 2019).

‡ Note that we also verify the goodness of fit (i.e. the residual diagnostics) of our ARMA-GARCH models by the the Box-Pierce statistic and find that our models can well capture the serial autocorrelation and the conditional heteroscedasticity in the returns of all financial institutions. Due to space limitations, we omit the estimated results and tests of the ARMA-GARCH models, which can be available upon request.

Table 1. Descriptive statistics of daily returns of 24 Chinese publicly listed financial institutions during the period from January 2, 2008 to December 28, 2018.

Ticker code	Financial institution	Abbr.	Mean	Max.	Min.	Std. Dev.	J-B	$BP^1(10)$	$BP^1(20)$	$BP^2(10)$	$BP^2(20)$
Panel A: Banks											
000001.SZ	Ping An Bank	PAB	– 0.0007	0.0957	– 0.1056	0.0261	888.6***	120.5177***	220.9183***	865.7241***	1340.1819***
002142.SZ	Bank of Ningbo	NBCB	0.0001	0.0960	– 0.1055	0.0244	1112.6***	15.5006	47.4889***	517.6080***	726.1077***
600000.SH	Shanghai Pudong Development Bank	SPDB	0.0001	0.0957	– 0.1057	0.0233	1969.7***	15.6884	38.1095***	1022.2784***	1764.3700***
600015.SH	Huaxia Bank	HXB	0.0002	0.0959	– 0.1059	0.0239	1431.9***	10.6933	32.5822**	949.2692***	1652.4640***
600016.SH	China Minsheng Banking Co., Ltd	CMBC	0.0000	0.0962	– 0.1054	0.0214	1994.1***	22.2336**	48.1914***	801.9595***	1187.3957***
600036.SH	China Merchants Bank	CMB	0.0000	0.0955	– 0.1054	0.0221	1678.2***	14.8085	36.4733**	916.1727***	1483.6987***
601009.SH	Bank of Nanjing	NJBK	0.0002	0.0959	– 0.1055	0.0228	1633.9***	25.0522***	42.6280***	760.8053***	1111.0275***
601166.SH	Industrial Bank	CIB	0.0000	0.0958	– 0.1056	0.0236	1622.2***	17.0888*	44.0929***	824.4678***	1382.7781***
601169.SH	Bank of Beijing	BOB	0.0002	0.0958	– 0.1055	0.0219	2075.9***	12.5216	29.3563*	708.1579***	1106.9765***
601328.SH	Bank of Communications	BOCOM	0.0000	0.0963	– 0.1060	0.0205	3630.9***	36.5539***	76.7656***	1020.2938***	1533.1443***
601398.SH	Industrial and Commercial Bank of China	ICBC	0.0001	0.0958	– 0.1054	0.0172	5293.5***	54.4627***	76.5194***	1091.5605***	1242.2834***
601939.SH	China Construction Bank	CCB	0.0001	0.0957	– 0.1064	0.0185	3532.3***	27.7108***	66.7412***	1234.1626***	1599.2902***
601988.SH	Bank of China	BOC	– 0.0001	0.0968	– 0.1058	0.0169	5929.8***	26.3313***	54.6456***	1044.3045***	1607.9833***
601998.SH	China CITIC Bank	CNCB	– 0.0003	0.0961	– 0.1056	0.0232	1531.3***	24.7835***	44.6495***	699.6811***	953.4407***
Panel B: Securities											
000686.SZ	Northeast Securities	NESC	– 0.0007	0.0956	– 0.1056	0.0324	446.7***	17.4920*	37.7285***	994.5776***	1686.4613***
000728.SZ	Guoyuan Securities	GYSC	– 0.0004	0.0955	– 0.1055	0.0320	596.4***	24.9292***	37.7204***	1273.7226***	2128.7110***
000783.SZ	Changjiang Securities	CJSC	– 0.0006	0.0961	– 0.1063	0.0316	586.8***	38.4615***	51.3459***	1270.6738***	1969.3369***
600030.SH	CITIC Securities	CITICS	– 0.0001	0.0957	– 0.1055	0.0281	855.6***	24.9262***	40.1986***	896.6628***	1342.5299***
600109.SH	Sinolink Securities	SLSC	– 0.0004	0.0958	– 0.1057	0.0328	453.9***	22.2058**	41.4741***	1212.6443***	1783.2022***
600837.SH	Haitong Securities	HTSEC	– 0.0005	0.0958	– 0.1056	0.0300	900.0***	23.8575***	45.6354***	1792.9317***	3285.3686***
601099.SH	Pacific Securities	PSC	– 0.0008	0.0965	– 0.1057	0.0309	672.2***	23.3490***	40.7710***	1426.1654***	2395.2846***
Panel C: Insurances											
601318.SH	Ping An Insurance	PAI	– 0.0003	0.0955	– 0.1054	0.0242	980.2***	19.6987**	52.9951***	679.7901***	1178.9247***
601601.SH	China Pacific Insurance	CPIC	– 0.0001	0.0956	– 0.1054	0.0252	518.4***	23.8286***	58.6126***	458.5424***	794.5938***
601628.SH	China Life Insurance	CLI	– 0.0003	0.0956	– 0.1054	0.0242	1074.4***	26.3339***	65.0843***	898.5976***	1498.1874***

Notes: J-B denotes the Jarque-Bera statistic for testing the null hypothesis of normal distribution. $BP^1(l)$ and $BP^2(l)$ are the Box-Pierce statistics for testing the null hypothesis of no serial autocorrelation at lag l in the returns and the squared returns, respectively. ***, **, and * denote the significance levels at 1%, 5%, and 10%, respectively.

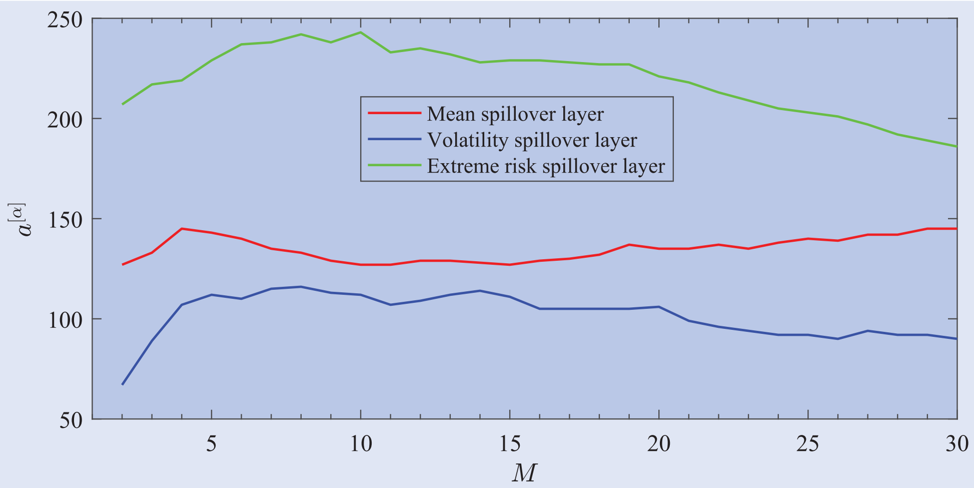

Figure 1. Degree of each layer in multilayer spillover networks as functions of lag order M.

4.2.1. Results for similarity measures. Our proposed multilayer information spillover networks measure the interconnectedness of financial institutions by taking account of three different information spillover effects, including mean spillover effect, volatility spillover effect and extreme risk spillover effect. In order to explore whether there is similarity among different information spillover layers, we study the basic network characters of each layer, e.g. the degree of each layer.

Figure 1 shows the degree of each layer under different lag orders M. Extreme risk spillover layer has more interconnected edges than mean and volatility spillover layers at different lags. The strong interconnectedness on extreme risk spillover layer may relate to the sample period we investigated, because it includes several stressful events, e.g. the European sovereign debt crisis and the '2015–2016 Chinese stock market turbulence.' The degree of each layer increases rapidly when the lag order increases from 2 to 5, then the growth rate slows down and the degree tends to be stable. When the lag order is at a high value (i.e. $M \geq 20$), the degrees of extreme risk and volatility spillover layers begin to decrease, while the degree of mean spillover layer shows a slightly upward trend. This pattern suggests that the market needs time to respond to past information, and needs at least 5 days to fully digest the information (see figure 1).† In our following empirical study, if there are no special instructions, we set the lag order $M = 10$, which corresponds to the 10-day VaR required by the Bank for International Settlements (Diebold and Yilmaz 2014, Wang *et al.* 2017). Besides, the degree of each layer when $M = 10$ is at a high level and relatively stable, and thus the networks at this lag can fully reflect the past information.

To visualize the networks, figure 2 shows a snapshot of multilayer information spillover networks when $M = 10$. We notice that the interconnectedness of financial institutions at each layer is not consistent. For example, Pacific Securities (PSC) has strong correlations with other institutions on extreme risk spillover layer, but its correlations with others on mean and volatility spillover layers are both weak. China Life Insurance (CLI) has a strong spillover effect to other institutions on volatility spillover layer, but weak on mean and extreme risk spillover layers.

Figure 3 shows dynamic degree of each layer in time-varying multilayer information spillover networks. We find some similarities as well as differences among the three layers. The overall trend of the degrees among the three layers is relatively consistent. When the degree of a layer increased and reached the peak, the degrees of other layers changed almost synchronously, e.g. in the periods of mid-2011, the end of 2016, the end of 2017, and the first and second quarters of 2018, indicating that the increased interconnectedness of financial institutions measured by different information spillover effects is consistent. However, it is worth noting that during the period from 2014 to 2016, the peaks of the degree on the three layers show nonsynchronous, in which extreme risk spillover layer first reached the peak, followed by volatility and mean spillover layers. Specifically, the degree of extreme risk spillover layer peaked in the early Chinese bull market of 2014–2015, and the degree peak of volatility spillover layer appeared on the eve of the Chinese stock market crash, while the highest point of the degree of mean spillover layer just occurred during the '2015–2016 Chinese stock market turbulence.' We thus conclude that extreme risk spillover layer and volatility spillover layer can provide early warning signals of financial stress or crisis, while mean spillover layer generally has hysteresis relative to the other two layers, reaching its degree peak during or after the outbreak of a crisis. In the early European sovereign debt crisis (2009–2010) the dynamic degree pattern of three layers also showed the nonsynchronous effect and the sequential lag phenomenon. Further, we compute Pearson's correlation coefficients between dynamic degree series of three layers,

† Note that the results about the degree of each layer under different lag orders M by using the Bonferroni correction (i.e. β') are slightly different from our original results using β. When the lag order increases from 2 to 5, only the degree of mean and volatility spillover layers increases rapidly. The degree of extreme risk spillover layer always shows a downtrend as the lag order increases. When $M \geq 10$, the degree of volatility spillover layer stands at a stable state. When the lag order is at a high value (i.e. $M \geq 20$), the degree of mean spillover layer shows a slightly downtrend instead of a rising tide. Thus, we conclude that the lag order M cannot be selected too small especially when measuring mean and volatility spillover effects.

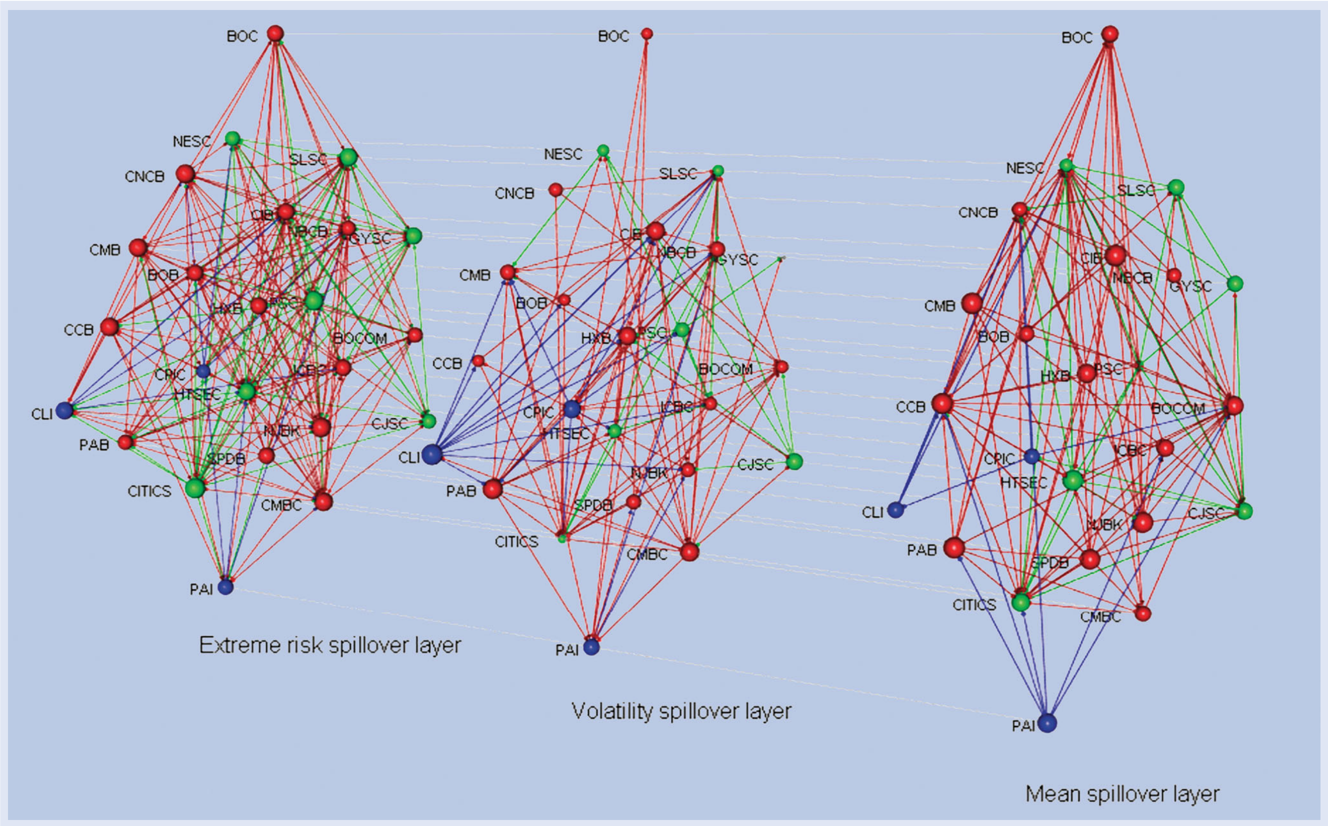

Figure 2. A snapshot of multilayer information spillover networks of 24 Chinese publicly listed financial institutions during the period 2008–2018, when $M = 10$. Notes: the first layer, the second layer and the third layer (from right to left) are corresponding to mean spillover layer, volatility spillover layer and extreme risk spillover layer, respectively. The node label is the abbreviation of financial institution in table 1. The node's size is proportional to the node's degree. The node's color represents different industry attributes, where red, green and blue are corresponding to banks, securities and insurances. The color of the edge is consistent with the industry color of the sender of the spillover effect.

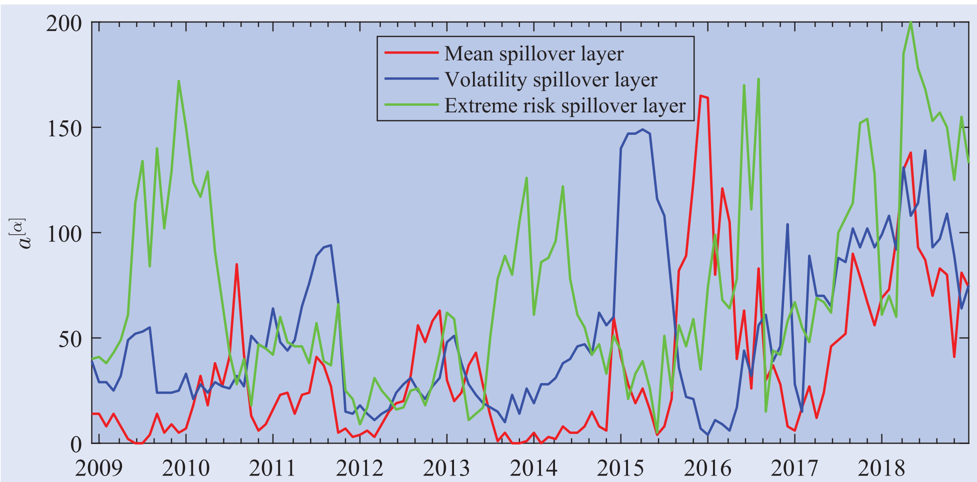

Figure 3. Dynamic degree of each layer in time-varying multilayer information spillover networks.

and find the correlation coefficients fall in the range of [0.19, 0.31]. In summary, we have the following conclusions: (i) the correlations among three information spillover layers are weak, and (ii) the interconnectedness among financial institutions varies greatly on layers, namely, three layers have heterogeneous interconnectedness structure.

Financial institutions with strong interconnectedness or influence tend to receive more attention due to 'too interconnected to fail.' Thus, it is worth studying whether the influence of financial institutions on all layers in multilayer information spillover networks is similar. Here we use the degree of a financial institution on a layer to represent its interconnectedness or influence, because a financial institution has a large degree, suggesting that it has a great correlation or influence with or on other financial institutions on the given layer. We calculate the rank correlations between three different layers based on 24 financial institutions' degrees using Spearman's correlation coefficient. Figure 4 shows the degree

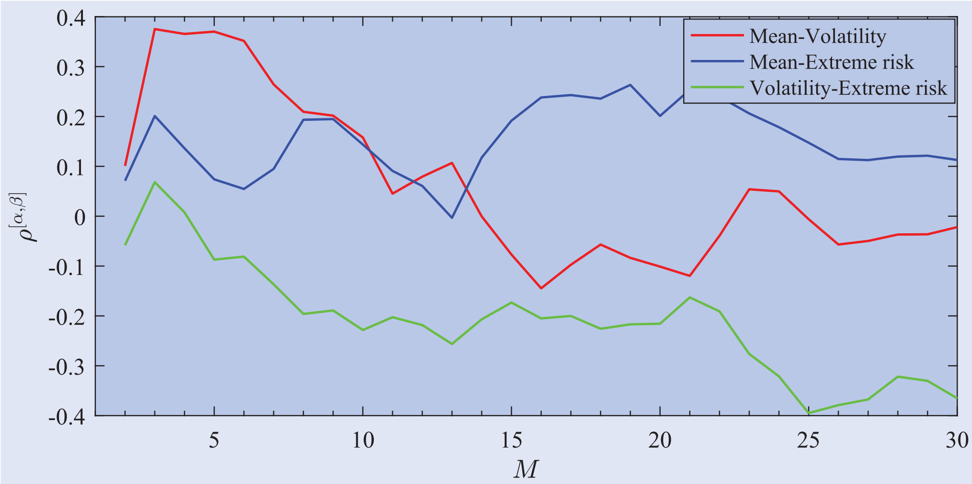

Figure 4. Spearman's correlation coefficients between three different layers based on 24 financial institutions' degrees in multilayer spillover networks as functions of lag order *M*.

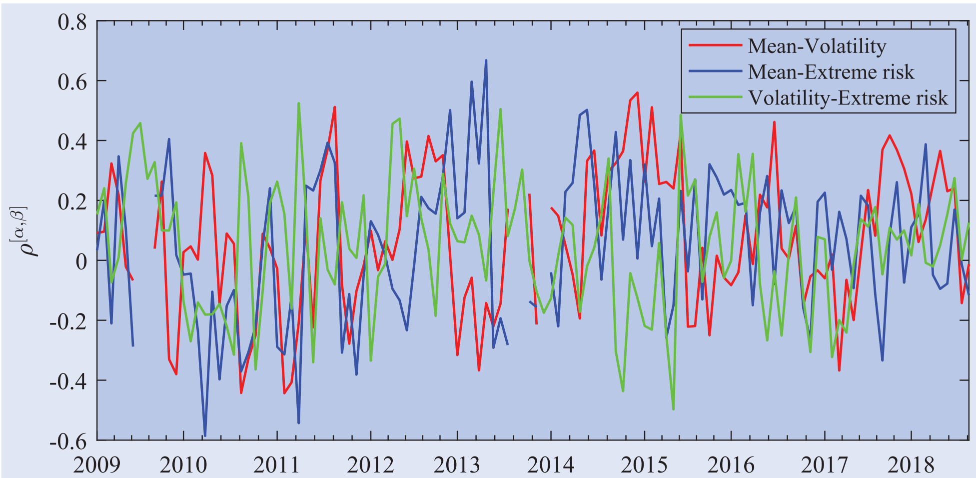

Figure 5. Dynamic Spearman's correlation coefficients between three different layers based on 24 financial institutions' degrees in time–varying multilayer information spillover networks. Note that the breakpoints in the figure are due to the absence of mean spillover effect in the corresponding window period, i.e. the 24 financial institutions are not connected on mean spillover layer.

rank correlations between three layers at various lag orders. We find that (i) the correlation between volatility spillover layer and extreme risk (or mean) spillover layer is decreasing when $M \geq 5$, (ii) the correlation between volatility spillover layer and extreme risk spillover layer is mainly negative, but the correlation is not large, and (iii) the correlation between mean spillover layer and extreme risk spillover layer changes little across the lag orders, but the correlation is very weak, with the maximum of 0.263. Figure 5 shows the dynamic rank correlations between three layers based on 24 financial institutions' degrees in time-varying multilayer information spillover networks. The dynamic correlations vary with time, but in most of the time the correlations fall between -0.2 and 0.2. Among the three pairs of dynamic correlations, those between mean spillover layer and extreme risk spillover layer have the largest fluctuation, with a maximum of 0.525 and a minimum of -0.497. This indicates that there is a certain dynamic correlation between different layers, but the overall correlation is not large, which may be related to different perspectives of measurements on different layers. In general, the correlations between three layers are weak, and the interconnectedness of financial institutions on each layer is quite different in multilayer information spillover networks.

4.2.2. Results for uniqueness measures. Our above study finds that the similarity between different layers is not strong. We here introduce unique edges to capture the peculiarity or difference among three layers. The unique edges on layer α mean the edges only exist on layer α rather than on other layers. Figure 6 shows a snapshot of unique edges in multilayer information spillover networks when $M = 10$. We notice that each layer has unique edges. Thus, some interconnections of financial institutions, i.e. unique edges on a certain layer, will not be captured if the layer is missing, which further demonstrates the indispensability of each layer and the importance of studying multilayer information spillover networks.

Figure 7 presents the number of unique edges on each layer under different lag orders. The curve or trend of the number of unique edges on each layer at different lags is quite similar to the degree curve or trend on the corresponding layer. We also notice that the number of unique edges of each layer

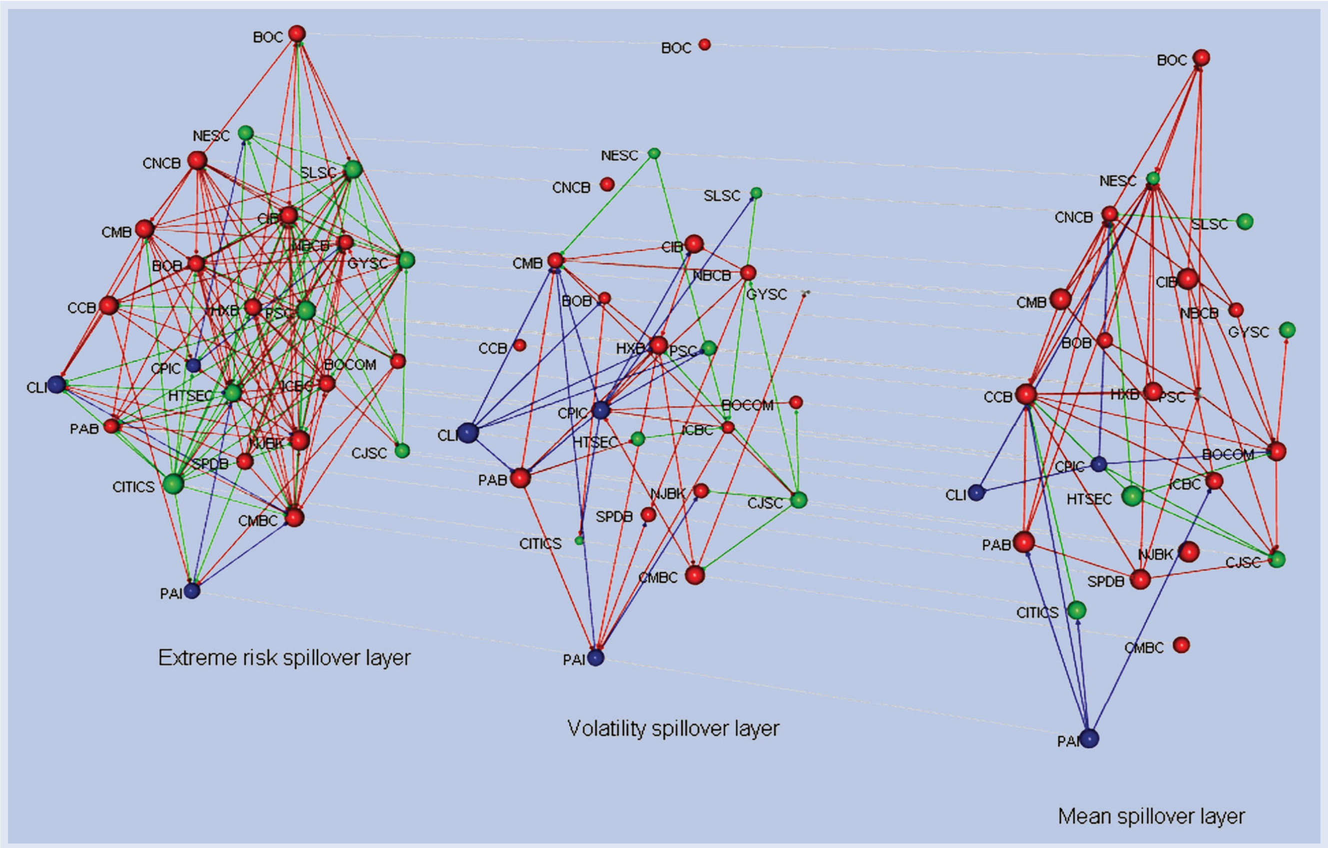

Figure 6. A snapshot of unique edges in multilayer information spillover networks of 24 Chinese publicly listed financial institutions during the period 2008–2018, when $M = 10$. Notes: a snapshot of the corresponding multilayer information spillover networks is shown in figure 2. The first layer, the second layer and the third layer (from right to left) are corresponding to mean spillover layer, volatility spillover layer and extreme risk spillover layer, respectively. The node label is the abbreviation of financial institution in table 1. The node's color represents different industry attributes, where red, green and blue are corresponding to banks, securities and insurances. The color of the edge is consistent with the industry color of the sender of the spillover effect.

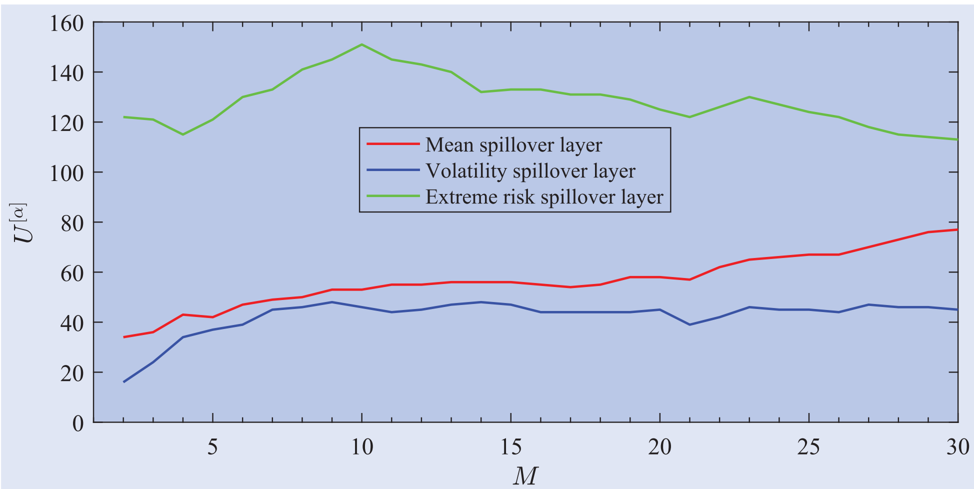

Figure 7. The number of unique edges on each layer in multilayer spillover networks as functions of lag order M.

slows down and tends to be stable when $M \geq 5$. In figure 8, we examine dynamic results for the number of unique edges on each layer in time-varying multilayer information spillover networks when $M = 10$. From figure 8, we observe that each layer of multilayer information spillover networks can capture unique links among financial institutions, but most of the time extreme risk spillover layer captures the largest number of unique edges, and mean spillover layer captures the fewest number of unique edges, sometimes even zero. The trend of the number of unique edges on each layer in dynamic multilayer information spillover networks is almost the same as the trend of the degree on the corresponding layer (see figures 3 and 8). Therefore, we consider that the increase or decrease in the number of edges on each layer in multilayer information spillover networks is mainly due to the increase or decrease in the number of the unique edges, i.e.the unique

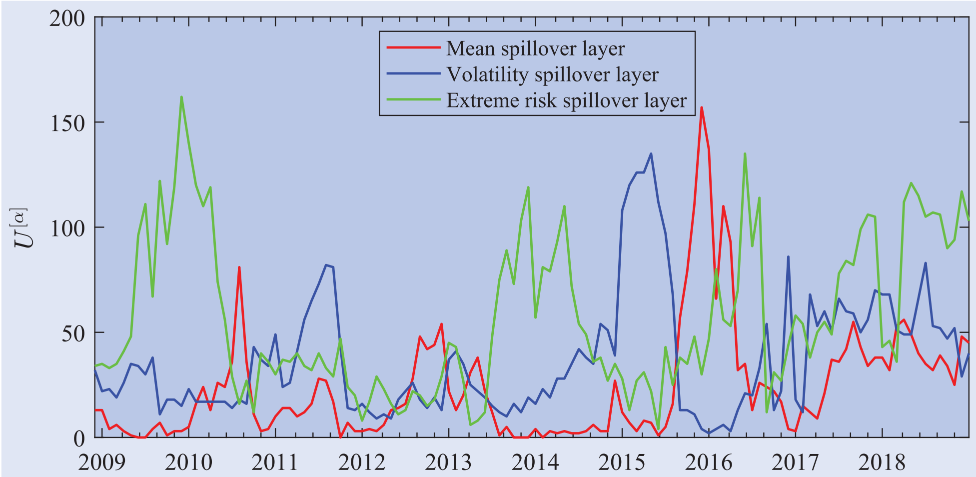

Figure 8. Dynamic number of unique edges on each layer in time-varying multilayer information spillover networks.

edges determine the network structure of each layer. Thus, regulators can focus on whether there are significant changes in unique edges on different layers to monitor the stability of the system.

From an institution-level perspective, figure 9 shows the unique edges of financial institutions on each layer at different lag orders. We notice that a significant increase in the number of unique edges of a financial institution generally occurs when the lag order is larger than 5 days (i.e. $M \geq 5$). We also find (i) that unique edges of financial institutions on each layer are different and change with the lag order, and (ii) that some financial institutions always have a large number of unique edges (i.e. the high interconnectedness with other institutions) on a certain layer across most of lag orders, e.g. China Merchants Bank (CMB) and Ping An Insurance (PAI) on mean spillover layer, Changjiang Securities (CJSC) on volatility spillover layer, and CITIC Securities (CITICS) and PSC on extreme risk spillover layer. Further, we list the top ten financial institutions according to the number of unique edges on each layer when $M = 10$ in table 2. We find that (i) financial institutions on extreme risk spillover layer have the largest number of unique edges, while financial institutions on mean and volatility spillover layers have a fewer unique edges, and (ii) the number of unique edges of banks is very large on each layer, suggesting the importance of banks. For example, the top 10 financial institutions on mean spillover layer, except for Haitong Securities (HTSEC) and PAI, are all banks. On volatility and extreme risk spillover layer, 7 of the top 10 financial institutions are banks.

Then we explore the evolution for the number of unique edges of 24 financial institutions on each layer, as shown in figures 10–12.† The dynamic patterns of unique edges on three layers also show the nonsynchronous effect during the financial turmoil. For example, a significant increase in the number of unique edges on extreme risk spillover layer happened prior to the early period of the European sovereign debt crisis (2009–2010) and during the '2015–2016 Chinese stock market turbulence,' followed by the increase on volatility spillover layer, while the increase on mean spillover layer occurred at the time of the above two crises outbreak or later.

At the beginning of our research period, lots of banks had more unique connections on the extreme risk spillover layer, and had a fewer number of unique edges on mean and volatility spillover layers. Sinolink Securities (SLSC) had a lot of unique edges on volatility spillover layer, but which was not significant on other layers. On mean spillover layer, almost all financial institutions, except for HTSEC, did not have a large number of unique edges.

After the beginning of the European debt crisis, there was another wave of increasing in unique edges. On extreme risk spillover layer, almost all banks, some securities, such as CITICS and PSC, and insurances had significantly increased in unique edges. Then on volatility spillover layer, the unique edges of CITICS and Northeast Securities (NESC) also increased. Subsequently, almost all financial institutions except for Ping An Bank (PAB) had an increased number of unique edges on mean spillover layer. This indicates that the mean spillover effect is more widespread than other two spillover effects during the crisis. In mid-2011, most of financial institutions had a significant increase in unique edges on the three layers, coincided with the most serious period of the European debt crisis.

In June 2013, banks' unique edges on extreme risk spillover layer increased significantly, especially the big state-owned commercial banks (ICBC, CCB, BOC, and BOCOM), China Minsheng Banking Co., Ltd (CMBC) and Shanghai Pudong Development Bank (SPDB). At that time, commercial banks were short of money and the liquidity of the interbank market was tense, coincided with 'the Chinese banking liquidity crisis of 2013,' which amplified the extreme risk spillover effect from banks to other financial institutions.

† Note that in the framework of financial network analysis, the centrality of nodes is related to financial institutions' interconnectedness and the ability of information transmission in the financial system. Thus, we also investigate the degree centrality of nodes (i.e. 24 financial institutions) on each layer and find that the dynamic patterns of node degrees are similar to those of the number of unique edges of nodes, suggesting that on different layers the interconnectedness trends or the information spreading capability of financial institutions are mainly affected by their the number of unique edges. This finding further confirms our previous point that the increase or decrease in the number of edges on each layer in multilayer information spillover networks is mainly due to that of the unique edges. The detailed results on dynamic node degrees can be available upon request.

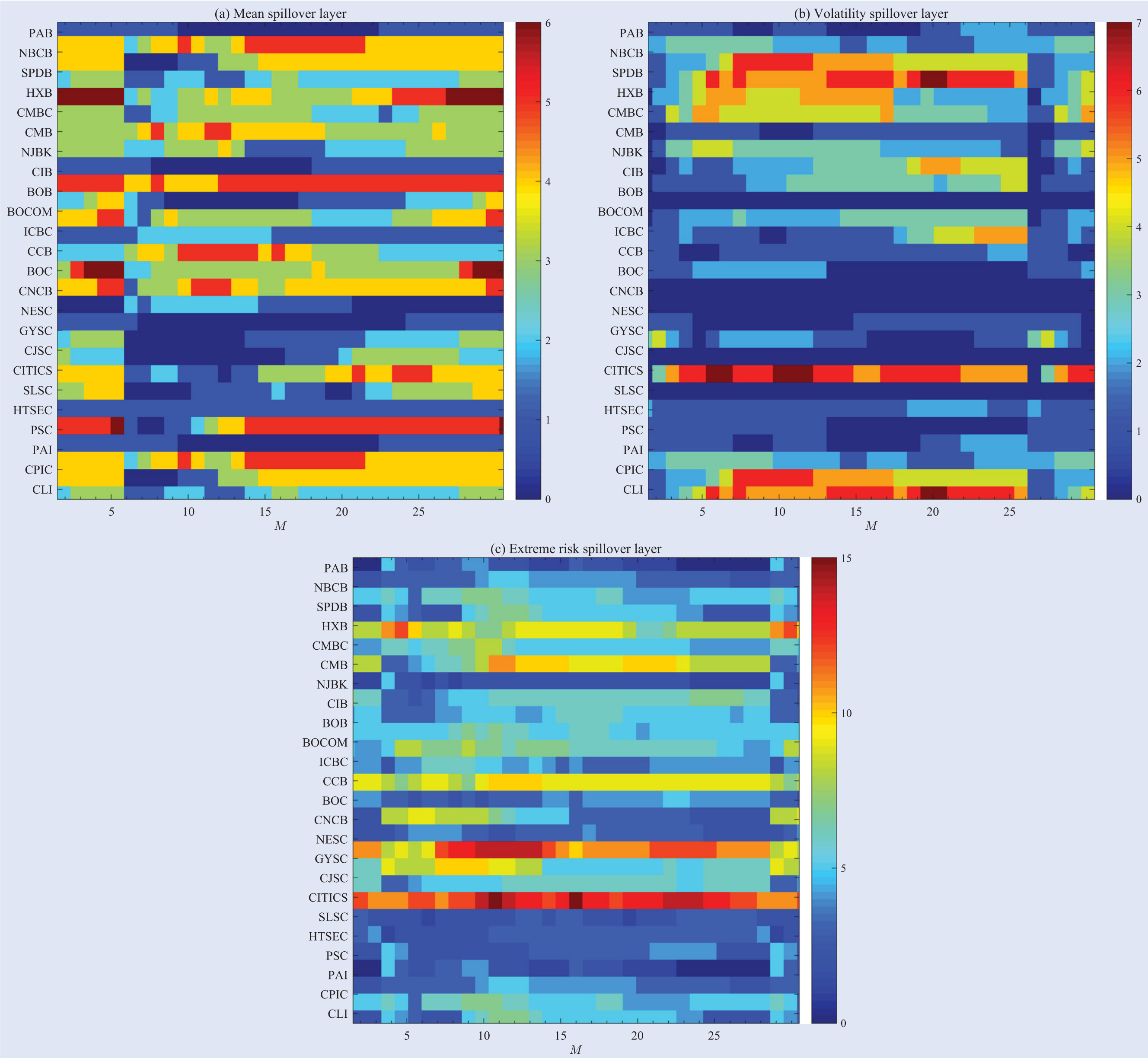

Figure 9. The number of unique edges of each financial institution on each layer in multilayer information spillover networks as functions of lag order M.

Table 2. Top 10 financial institutions ranked by the number of unique edges on each layer in multilayer information spillover networks when $M = 10$.

	Mean spillover layer		Volatility spillover layer		Extreme risk spillover layer	
Ranking	Name	# unique edges	Name	# unique edges	Name	# unique edges
1	CMB	5	CJSC	6	PSC	15
2	BOCOM	5	CPIC	6	CITICS	14
3	PAB	4	CLI	5	NJBK	11
4	SPDB	4	PAB	4	CNCB	10
5	CCB	4	NBCB	4	SLSC	9
6	HTSEC	4	HXB	3	CMB	8
7	PAI	4	PAI	3	SPDB	7
8	NBCB	3	CMBC	2	HXB	7
9	HXB	3	CMB	2	CMBC	7
10	CIB	3	CIB	2	ICBC	7

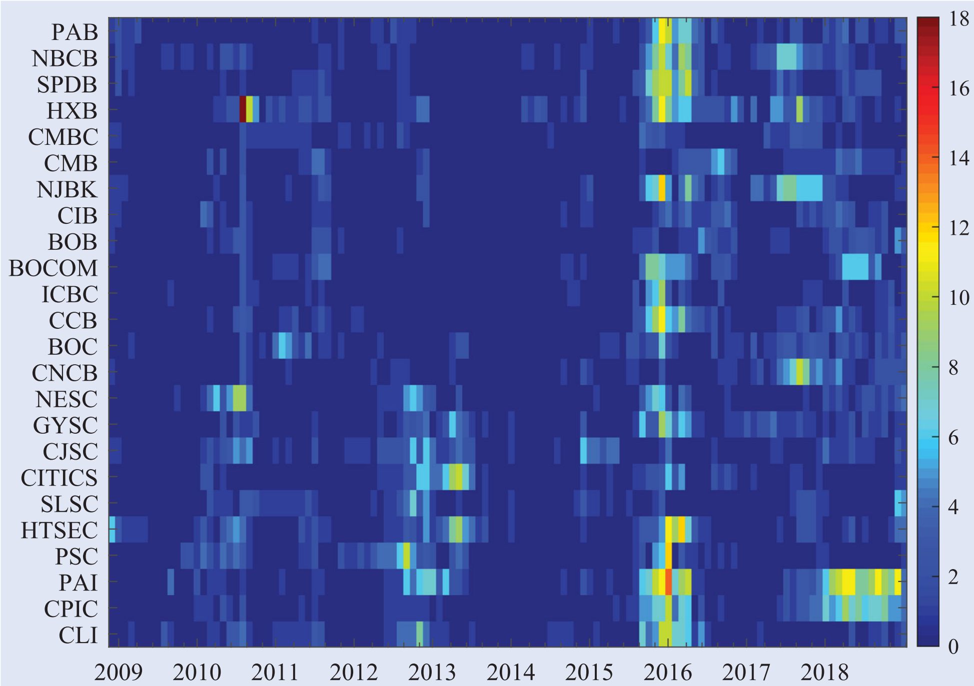

Figure 10. Dynamic evolution for the number of unique edges of financial institutions on mean spillover layer in time-varying multilayer information spillover networks.

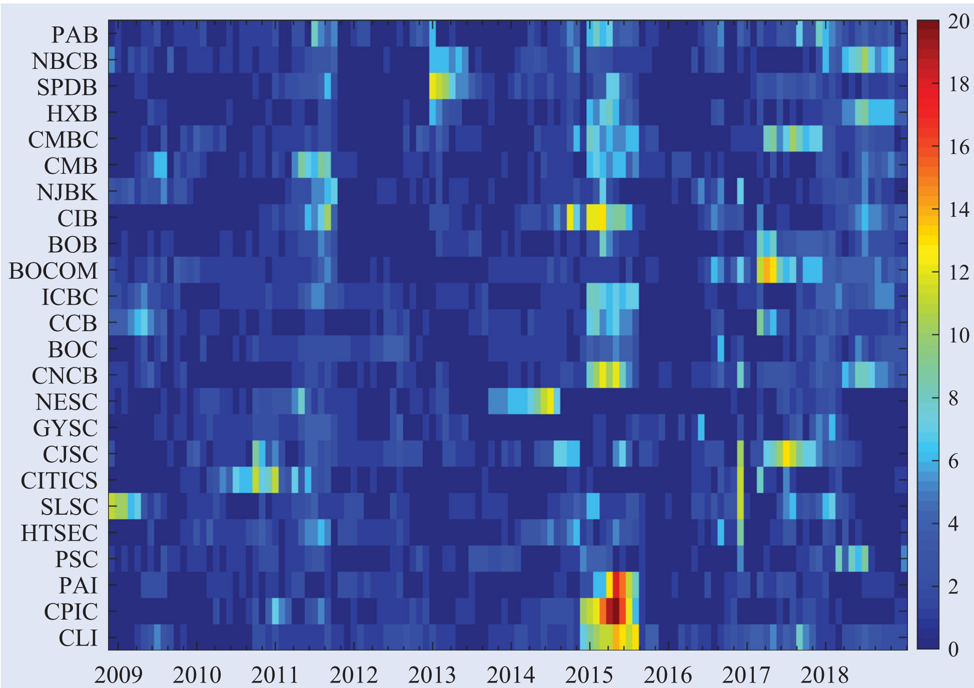

Figure 11. Dynamic evolution for the number of unique edges of financial institutions on volatility spillover layer in time-varying multilayer information spillover networks.

At the beginning of the bull market in the Chinese stock market in 2014, most of financial institutions showed many unique edges on extreme risk spillover layer. Most of the banks had more than 10 unique edges, reaching the peak record of the observation period. Then in early 2015, almost all banks (except for BOCOM and CMB), securities (except for NESC), and insurances increased their unique edges on volatility spillover layer. The increase in unique edges of banks and insurances continued until the beginning of stock market disaster (June 2015). During the stock market crash in 2015, unique edges of almost all financial institutions increased on mean spillover layer, except for China CITIC Bank (CNCB), CMB, CJSC, and SLSC. The number of financial institutions with increasing unique edges during the stock market crash in 2015 was significantly larger than that during the European debt crisis, suggesting that the impact of the 2015 stock market crash on the interconnectedness of financial institutions in China is stronger than that of the European debt crisis.

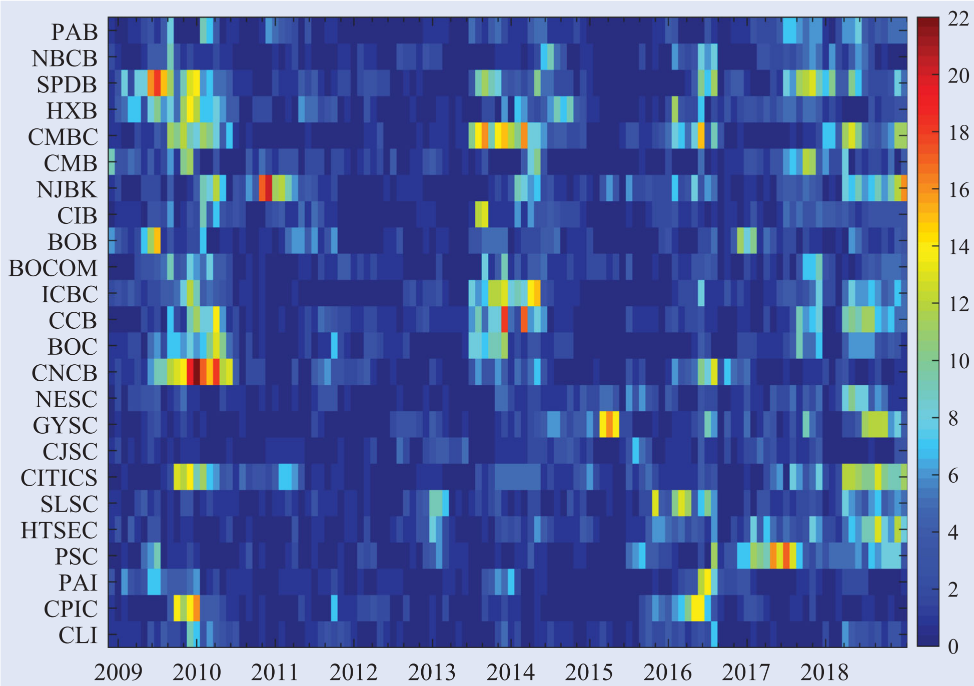

Figure 12. Dynamic evolution for the number of unique edges of financial institutions on extreme risk spillover layer in time-varying multilayer information spillover networks.

From mid-2017 to 2018, we have the following findings on each layer: (i) unique edges of almost all financial institutions except for three insurances increased on extreme risk spillover layer, (ii) on mean spillover layer, PAI and China Pacific Insurance (CPIC) had the largest number of unique edges, which lasted until the end of the observation period, and (iii) on volatility spillover layer, the top institutions ranked by the number of unique edge are mainly banks.

Before the financial turbulence, the increase in unique edges of financial institutions first occurs on extreme risk spillover layer, followed by volatility spillover layer, while the increase on mean spillover layer generally happens during the crisis. One possible reason or explanation why the increase in unique edges occurs on extreme risk spillover layer before the crisis is that the pre-crisis period is generally a period of the economic expansion, and at this time the economy is extremely active and financial innovations (e.g. new financial tools) develop rapidly, leading to highly interconnected financial institutions in the financial system. As a result of the extensive use of financial derivatives in the financial system, the leverage ratio increased, which laid a hidden danger for the healthy development of financial institutions. Thus, when a financial institution has a large loss, it is easy to affect other financial institutions (e.g. its counterparties) so that other financial institutions suffer huge losses, and this process is known as risk spillover or contagion among financial institutions. Therefore, the increase in the interconnectedness on extreme risk spillover layer often has a predictive function and can provide early warning signals for the crisis.

4.2.3. Results for overlap measures. In addition to considering the unique edges, we also take into account the non-unique edges of financial institutions through the projection network of multilayer information spillover networks.

In figure 13, we show a snapshot of the projection network of multilayer information spillover networks when $M = 10$ to understand the full information of multilayer networks, because the projection network captures the integrated interconnection information of three layer networks in the financial system.

Based on the concept of the projection network, we measure the average edge overlap of multilayer information spillover networks under different lag orders, as shown in figure 14. The average edge overlap shows an increasing trend when the lag order M is less than 5, and then is decreasing when $M \geq 5$. The average edge overlap is in a stable state when $9 \leq M \leq 21$, and then drops abruptly to a lower stable value. The change or trend of the average edge overlap when $M < 5$ indicates that the market or financial institutions do not fully respond to the past information and the contribution for the increasing interconnectedness should be mainly attributed to the increase of common edges rather than unique edges on each layer. When $M \geq 5$, we notice that the number of edges on each layer in multilayer information spillover networks is at a stable level (see figure 1), but the average edge overlap shows a decreasing tendency. This implies that (i) the increase in the interconnectedness of financial institutions is attributed to the increase of unique edges and (ii) the heterogeneous information of each layer begins to appear when $M \geq 5$. The decrease in the average edge overlap when $M > 21$ may be due to the fact that the impact of the new or recent information will weaken when considering past information for a long period of time, so the information is insufficient under these lag orders. Thus, we consider that it is better to choose the lag order in the interval [9, 21] for studying the information spillover effects, and this supports our decision to construct time-varying multilayer information spillover networks with the lag order $M = 10$.

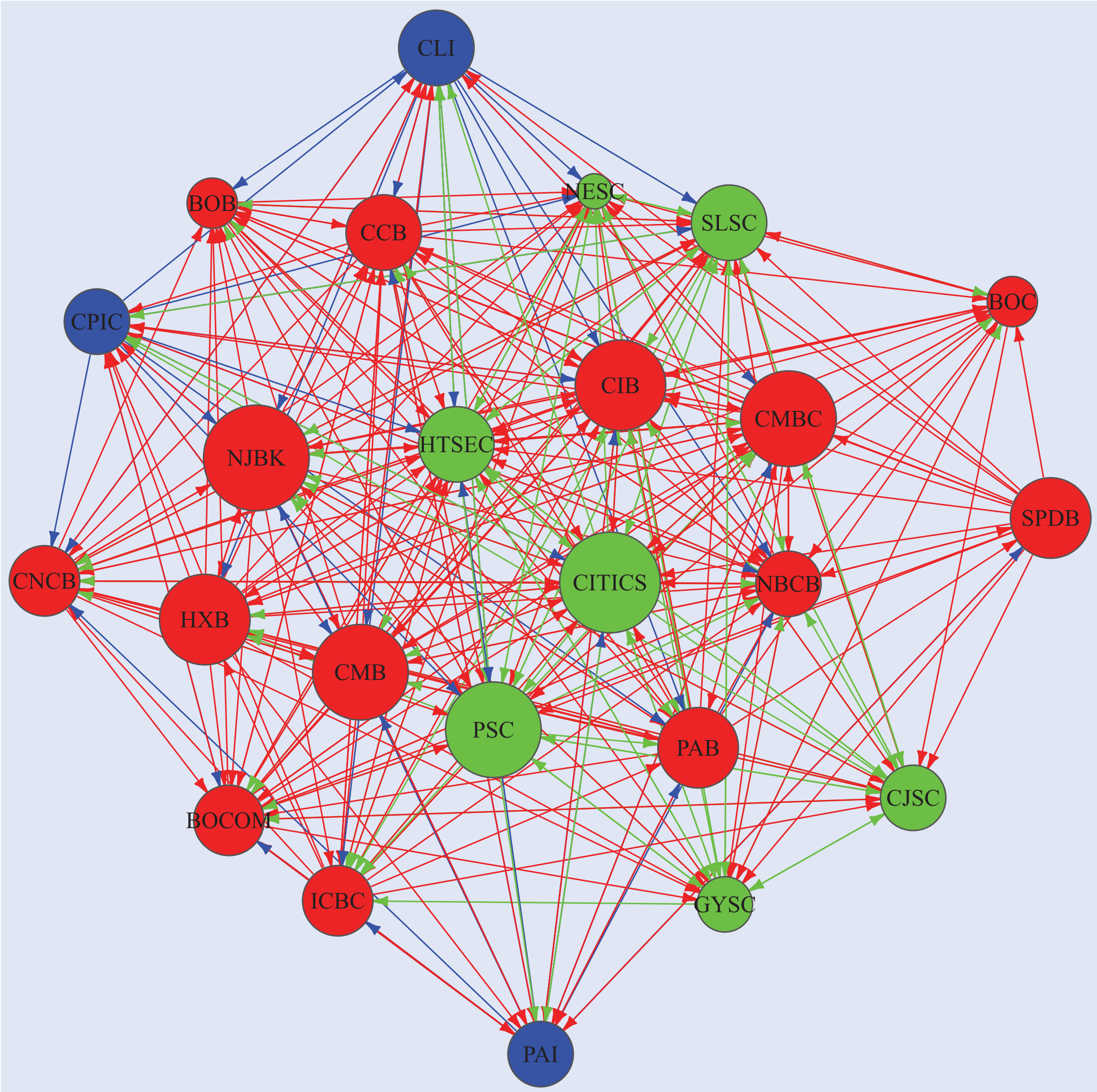

Figure 13. A snapshot of the projection network of multilayer information spillover networks linking 24 Chinese publicly listed financial institutions during the period 2008–2018, when $M = 10$. Notes: a snapshot of the corresponding multilayer information spillover networks is shown in figure 2. The node label is the abbreviation of financial institution in table 1. The node's size is proportional to the node's degree. The node's color represents different industry attributes, where red, green and blue are corresponding to banks, securities and insurances. The color of the edge is consistent with the industry color of the sender of the spillover effect.

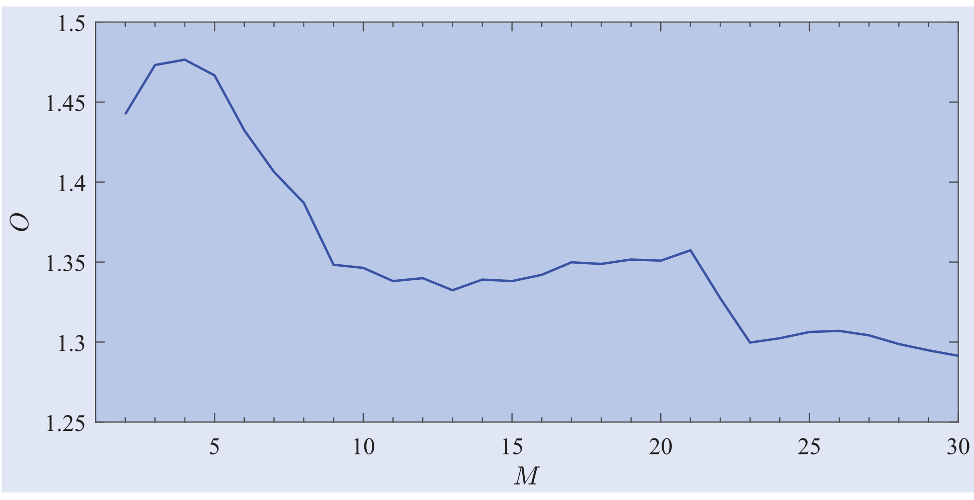

Figure 14. The average edge overlap of multilayer information spillover networks as a function of lag order M.

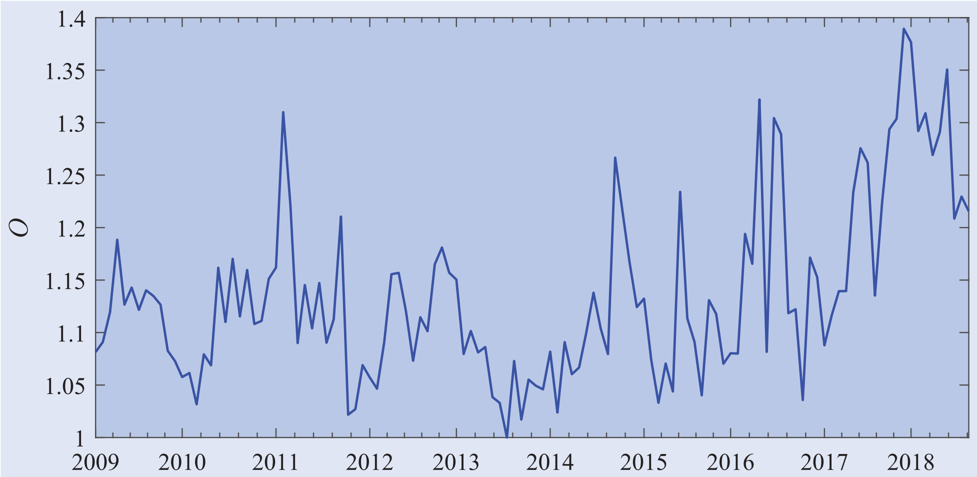

Figure 15. Dynamic average edge overlap of time-varying multilayer information spillover networks.

In figure 15, we show the dynamic average edge overlap of time-varying multilayer information spillover networks. We note that the average edge overlap is relatively low and less than 2, indicating that (i) on average each edge will not simultaneously appear on two layers and (ii) each information spillover layer has a complementary effect. Therefore, if we independently consider the three layers of multilayer information spillover networks, the obtained information is one-sided and cannot fully reflect the interconnectedness among financial institutions. We also find that the average edge overlap during the financial turmoil drops significantly and reaches a low point. In March 2010, the average edge overlap reached a minimum point, coincided with the fermentation period of the European sovereign debt crisis, when the Greece's sovereign debt crisis began to spread to the 'European Five.' The panic of the spreading debt crisis caused global stock markets to oscillate and brought enormous uncertainty to the recovering economy. In the money shortage period of June 2013, the average edge overlap was at the lowest point, reaching 1. When the average overlap of the multilayer information spillover network is 1, it means that the edges on each layer are unique and exist only on one layer. The special or heterogeneous interconnectedness of financial institutions can only be captured by a certain layer of multilayer information spillover networks, and cannot be captured by other layers. During the Chinese stock market disaster from 2015 to 2016, the average edge overlap also reached a minimum value. It is worth noting that when the average edge overlap reaches the minimum value, the number of edges in multilayer information spillover networks reaches the peak (see figure 3), which is consistent with our previous conclusion that the increasingly complex interconnectedness of financial institutions is mainly attributed to the increase of unique edges. The increase of unique edges causes the reduction of the average edge overlap. All in all, the differences among the three layers become significant during the financial turmoil.

To better identify relatively important financial institutions, we compute the overlapping degree of financial institutions, which is defined as the number of edges the node has to other nodes on all layers in multilayer information spillover networks. We first investigate the overlapping degree of financial institutions at different lag orders, as shown in figure 16. We find that (i) CMBC, CMB, Bank of Nanjing (NJBK), CIB, CITICS and PAI are highly connected with other financial institutions, because their overlapping degrees are large and they rank high in the sample across different lag orders, and (ii) the overlapping degrees of Bank of Ningbo (NBCB), Bank of Beijing (BOB), BOC and CPIC are relatively stable and small under different lag orders.

Further, in table 3, we list the top 10 financial institutions according to the overlapping degree in multilayer information spillover networks when $M = 10$, consisting of 6 banks, 3 securities and 1 insurances. We also report the top 10 financial institutions ranked by their degrees on each layer in table 3. NJBK and CMBC, as representatives of small and medium-sized banks, always occupy the top 1 or 2 either on each layer (see, the degree ranking) or in the multilayer networks (see, the overlapping degree ranking), suggesting that they have strong interconnectedness with other financial institutions and large systemic risk contributions to the financial system. Small and medium-sized banks usually have the higher operating leverage and higher asset quality risks (i.e. higher non-performing loan ratios) than large commercial banks. Thus, it is necessary to strengthen the supervision on these small and medium-sized banks to prevent the spread of risks. In June 2019, China International Capital Corporation (CICC), the biggest investment bank in China, downgraded stock ratings of NJBK, CMBC and other three small and medium-sized banks to neutral, aiming to increase investor awareness of risk to small and medium-sized banks. Although the results may be related to the number of financial institutions selected in the three industries in our research, the leading role of banks can be seen both in ratio and quantity. The strong interconnectedness of banks is also reflected on all layers (see table 3). This may be related to the facts (i) that the Chinese financial system is dominated by the banking industry, and (ii) that corporate financing or social financing is mainly through indirect financing from commercial banks, which prompt China's commercial banks to have the strong interconnectedness.

Figure 17 shows dynamic overlapping degrees of financial institutions in time-varying multilayer information spillover networks. The overlapping degrees of financial institutions change over time, and no financial institution always plays a central role. Note that since the end of 2017,

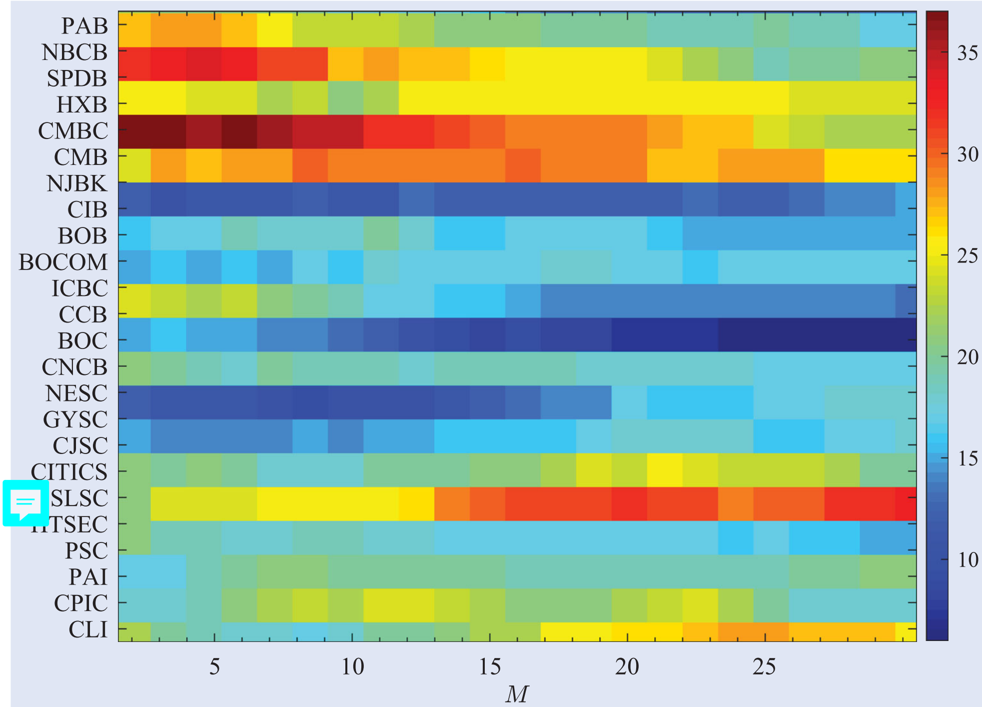

Figure 16. The overlapping degree of each financial institution in multilayer spillover networks as functions of lag order M.

Table 3. Top 10 financial institutions ranked by the node degree on each layer and overlapping degree in multilayer information spillover networks when $M = 10$.

	Mean spillover layer		Volatility spillover layer		Extreme risk spillover layer			
Ranking	Name	# degree	Name	# degree	Name	# degree	Name	Overlapping degree
1	NJBK	10	CMBC	11	NJBK	21	NJBK	35
2	CIB	10	CLI	11	CITICS	19	CMBC	31
3	PAB	8	PAB	10	PSC	19	CIB	30
4	SPDB	8	CIB	9	CMBC	16	CITICS	25
5	CMB	8	HXB	8	CNCB	13	PAB	23
6	BOCOM	8	CJSC	7	SLSC	13	HXB	23
7	HTSEC	8	CPIC	7	CMB	11	CMB	23
8	CCB	7	NBCB	5	CIB	11	PSC	23
9	HXB	6	PAI	5	CCB	11	CLI	22
10	PAI	6	SPDB	4	GYSC	11	HTSEC	21

the interconnectedness of financial institutions has generally increased, indicating the increasing possibility of systemic risk and the occurrence of systemic events, which have been somewhat verified by the recent events in 2018–2019. For example, on February 23, 2018, the China Insurance Regulatory Commission (CIRC)† announced to temporarily seize control of Anbang Insurance Group that claims 1.97 trillion yuan ($310.85 billion) in assets and ranks 139 on the Global Fortune 500 list in 2017, because Anbang had violated laws and regulations which 'may seriously endanger the solvency of the company.' Since May 24, 2019, Baoshang Bank, a city commercial bank, has been taken over by China's banking regulators for a year due to serious credit risks, according to a joint announcement by the People's Bank of China (PBoC) and the CBIRC. A event that a bank or insurer is taken over by the regulators in China is rare and seems serious. In history, only two similar events occurred in China's financial system, i.e. the bankruptcy of Hainan Development Bank in 1998 and the takeover of Shantou Commercial Bank in 2001. Thus it is worth noticing that the high level of interconnectedness among financial institutions in multilayer information spillover networks may provide a signal that the financial system is under a high stress.

The high overlapping degree of financial institutions may be the strong interconnection of financial institutions in a certain layer, or may be the superposition effect of each layer, so following de la Concha *et al.* (2017), we measure the participation coefficient to measure the distribution of the connection between financial institutions on layers. Figure 18 shows the time-varying participation coefficients of different financial institutions. The higher the participation coefficient is, the more homogeneous the distribution of financial institutions' activity is among layers. The distribution of institutions' activity varied with time, so it is not a common

† Note that the CIRC and the China Banking Regulatory Commission (CBRC) were combined into the China Banking and Insurance Regulatory Commission (CBIRC) on March 21, 2018.

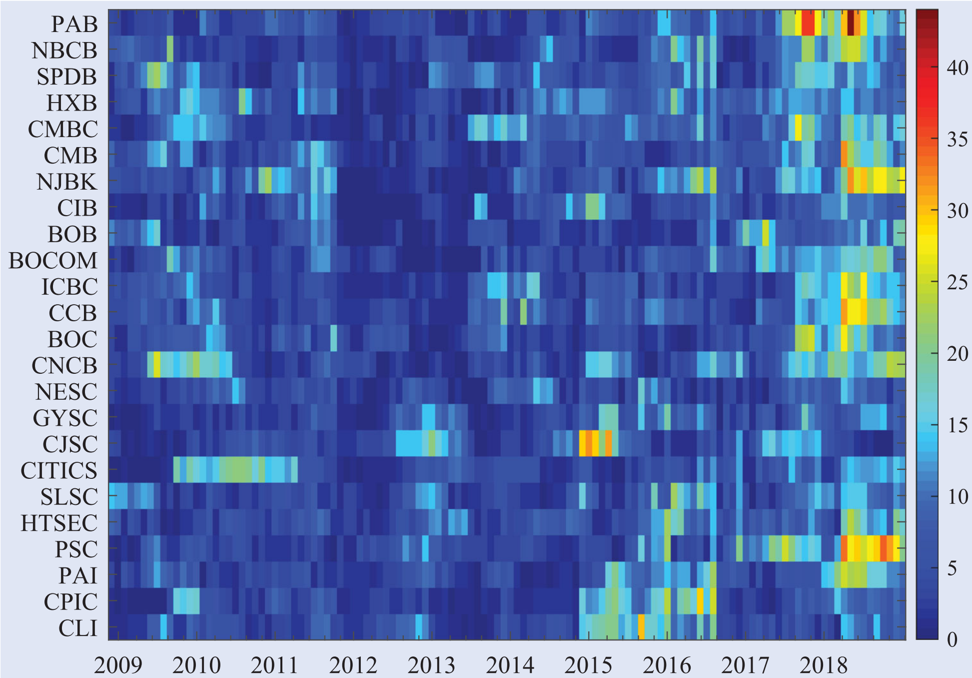

Figure 17. Dynamic overlapping degrees of financial institutions in time-varying multilayer information spillover networks.

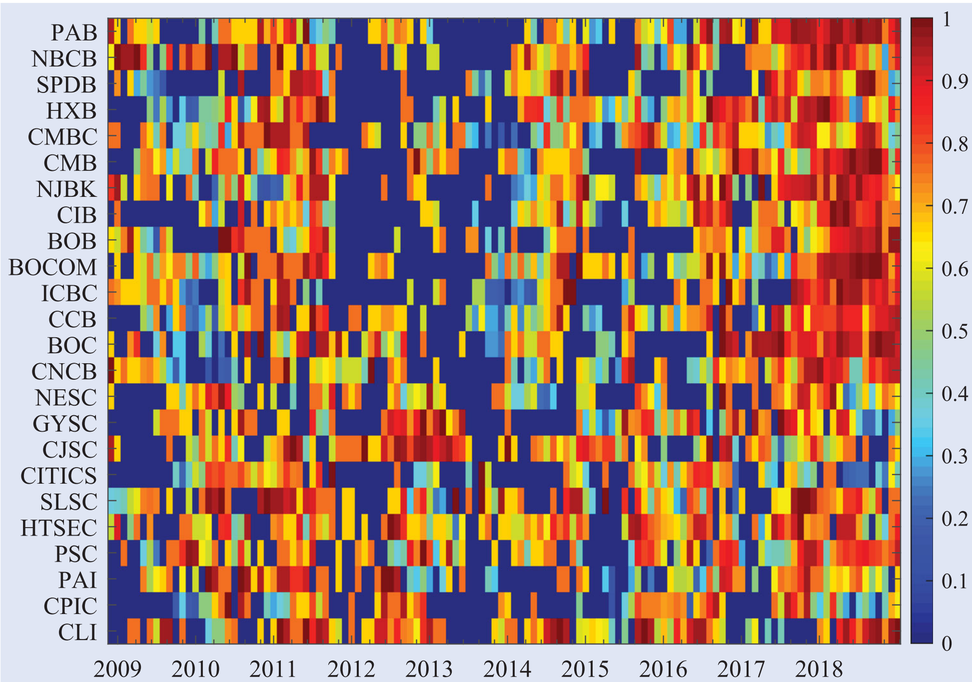

Figure 18. Dynamic participation coefficient of financial institutions in time-varying multilayer information spillover networks.

reason for an increase in overlapping degree, but we notice that the strong connection since the end of 2017 is due to the uniformly increasing interconnectedness on each layer.

5. Conclusions

We have proposed multilayer information spillover networks taking into account a mean spillover layer, a volatility spillover layer and an extreme risk spillover layer. Using the proposed multilayer networks, we have investigated the interconnectedness of 24 Chinese financial institutions from January 2, 2008 to December 28, 2018. We have measured the statistics between pairs of financial institutions corresponding to mean spillover, volatility spillover and extreme risk spillover based on the CCF-based Ganger causality tests in mean, volatility and risk, and then constructed static and dynamic multilayer information spillover networks based on the information spillover effects of the three aspects. Finally, we have used some multilayer measures to study the interconnectedness of financial institutions. Our findings fall into four categories.

(i) The peak degree on each layer of multilayer information spillover networks generally has a synchronization effect, but the overall similarity is very weak. In the financial turmoil, such as the beginning of European debt crisis and the '2015–2016 Chinese stock market turbulence,' however, there was a significant asynchronous effect among layers, and the degree peaks of the extreme risk spillover layer and volatility spillover layer appeared before the crisis, which can serve as an early warning signal. This phenomenon can also be captured by the unique edge of financial institutions on each layer.

(ii) The trend of the unique edge is the same as the trend of the degree, indicating that the increasing connection of financial institutions is mainly attributed to the rise of unique edges. Thus, regulators can focus on the changes of unique edges when monitoring the growing interconnectedness of financial institutions. The unique edge measure, referring to an edge that can only be captured by a specific layer, also suggests the importance of studying multilayer information spillover networks.

(iii) The average edge overlap is lower than 2 on average, so the information obtained by the network is one-sided no matter which layer is considered separately. Moreover, during financial turmoil, the average edge overlap will drop significantly, reaching a minimum point. By studying the overlapping degree, we conclude that relatively important financial institutions change over time. On the whole, banks have a high degree of overlap, which may be related to China's financial system dominated by the banking industry.

(iv) Financial institutions need at least 5 days to fully digest past information, and the impact of past information begins to weaken when $M \geq 20$. When the lag order is greater than 5, the heterogeneity of each layer begins to manifest itself, and then the heterogeneity is in the steady state when $9 \leq M \leq 21$. Therefore, we consider that it is better to choose the lag order of 9–21 when studying information spillover effects.

Our proposed multilayer spillover networks provide a new tool for investors and regulators, which can facilitate the choice of decentralized portfolio strategies and the supervision of financial institutions. The increased interconnectedness of different financial institutions at different layers indicates that the corresponding information spillover measure needs to be used to assess the risk and possible decentralization effects of a financial institution. Regulators can warn of possible financial turmoil by detecting the decrease of average edge overlap and the early arrival of the degree peak on the extreme risk spillover layer to achieve the purpose of preventing systemic risk.

Our work can be extended for further study. Because of the availability and validity of the sample, we only select 24 publicly listed financial institutions to investigate their interconnectedness, which does not comprehensively describe the interconnectedness in China's financial system. Besides, our proposed multilayer information spillover networks can be extended to measuring the interconnectedness of financial institutions in other national or international financial systems. When construing time-varying multilayer information spillover networks based on a rolling window analysis, we here choose the step size to be 20 for simplifying the calculation, due to the computational complexity of estimating the model. The robustness tests can be carried out further, and the step size can be gradually reduced to obtain more robust and definitive conclusions.

Acknowledgments

The authors thank two anonymous reviewers and the participants at the 2019 China Complex Economy Conference in Shanghai for helpful comments and suggestions.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by the National Natural Science Foundation of China [grant number 71871088], [grant number 71501066], [grant number 71971079], [grant number 71850006], [grant number 71521061], the Huxiang Youth Talent Support Program, and the Hunan Provincial Natural Science Foundation of China [grant number 2017JJ3024].

ORCID

Gang-Jin Wang http://orcid.org/0000-0002-2813-4356
Shuyue Yi http://orcid.org/0000-0001-8120-204X
Chi Xie http://orcid.org/0000-0003-3862-0224
H. Eugene Stanley http://orcid.org/0000-0003-2800-4495

References

Abbassi, P., Brownlees, C., Hans, C. and Podlich, N., Credit risk interconnectedness: What does the market really know?. *J. Financ. Stabil.*, 2017, **29**, 1–12.

Acharya, V.V., Pedersen, L.H., Philippon, T. and Richardson, M.P., Measuring systemic risk. *Rev. Financ. Stud.*, 2017, **30**, 2–47.

Adrian, T. and Brunnermeier, M.K., CoVaR. *Amer. Econom. Rev.*, 2016, **106**, 1705–1741.

Ahelegbey, D.F., Billio, M. and Casarin, R., Bayesian graphical models for structural vector autoregressive processes. *J. Appl. Econom.*, 2016, **31**, 357–386.

Ahelegbey, D., Billio, M. and Casarin, R., Sparse graphical multivariate autoregression: A Bayesian approach. *Ann. Econ. Stat.*, 2016, **123**, 1–30.

Aldasoro, I. and Alves, I., Multiplex interbank networks and systemic importance: An application to European data. *J. Financ. Stabil.*, 2018, **35**, 17–37.

Banulescu, G.D. and Dumitrescu, E.I., Which are the SIFIs? A component expected shortfall approach to systemic risk. *J. Bank. Financ.*, 2015, **50**, 575–588.

Bargigli, L., Di Iasio, G., Infante, L., Lillo, F. and Pierobon, F., The multiplex structure of interbank networks. *Quant. Finance*, 2015, **15**, 673–691.

Battiston, S., Farmer, J.D., Flache, A., Garlaschelli, D., Haldane, A.G., Heesterbeek, H., Hommes, C., Jaeger, C., May, R. and Scheffer, M., Complexity theory and financial regulation. *Science*, 2016, **351**, 818–819.

Betz, F., Hautsch, N., Peltonen, T.A. and Schienle, M., Systemic risk spillovers in the European banking and sovereign network. *J. Financ. Stabil.*, 2016, **25**, 206–224.

Bianchi, D., Billio, M., Casarin, R. and Guidolin, M., Modeling systemic risk with Markov switching graphical SUR models. *J. Econom.*, 2019, **210**, 58–74.

Billio, M., Getmansky, M., Lo, A.W. and Pelizzon, L., Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *J. Financ. Econ.*, 2012, **104**, 535–559.

Billio, M., Casarin, R. and Iacopini, M., Bayesian Markov switching tensor regression for time-varying networks. Working Paper, Ca' Foscari University of Venice, 2019, https://arxiv.org/abs/1711.00097.

Billio, M., Casarin, R., Kaufmann, S. and Iacopini, M., Bayesian dynamic tensor regression. Working Paper, Ca' Foscari University of Venice, 2019, https://arxiv.org/pdf/1709.09606.

Billio, M., Casarin, R. and Rossini, L., Bayesian nonparametric sparse VAR models. *J. Econom.*, 2019c, **212**, 97–115.

Boccaletti, S., Bianconi, G., Criado, R., Del Genio, C.I., Gómez-Gardeñes, J., Romance, M., Sendiña-Nadal, I., Wang, Z. and Zanin, M., The structure and dynamics of multilayer networks. *Phys. Rep.*, 2014, **544**, 1–122.

Box, G.E.P. and Pierce, D.A., Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *J. Am. Stat. Assoc.*, 1970, **65**, 1509–1526.

Brownlees, C.T. and Engle, R.F., SRISK: A conditional capital shortfall measure of systemic risk. *Rev. Financ. Stud.*, 2017, **30**, 48–79.

Buldyrev, S.V., Parshani, R., Paul, G., Stanley, H.E. and Havlin, S., Catastrophic cascade of failures in interdependent networks. *Nature*, 2010, **464**, 1025–1028.

Carpenter, J.N., Lu, F. and Whitelaw, R., The real value of China's stock market. NBER Working Paper No. 20957, New York University and MIT, 2015.

Casarin, R., Iacopini, M., Molina, G., Espinasa, R., Sucre, C. and Rigobon, R., Multilayer network analysis of oil linkages. *Econom. J.*, 2020, **23**, 269–296.

Chong, T.T.L., Lam, T.H. and Yan, I.K.M., Is the Chinese stock market really inefficient?. *China Econom. Rev.*, 2012, **23**, 122–137.

de la Concha, A., Martinez-Jaramillo, S. and Carmona, C., Multiplex financial networks: Revealing the level of interconnectedness in the banking system. In *Studies in Computational Intelligence (vol. 689)*, edited by C. Cherifi, H. Cherifi, M. Karsai, and M. Musolesi, pp. 1135–1148, 2017 (Springer Nature: Cham, Switzerland).

Demirer, M., Diebold, F.X., Liu, L. and Yilmaz, K., Estimating global bank network connectedness. *J. Appl. Econom.*, 2018, **33**, 1–15.

Diebold, F.X. and Yilmaz, K., On the network topology of variance decompositions: Measuring the connectedness of financial firms. *J. Econom.*, 2014, **182**, 119–134.

Diebold, F.X. and Yilmaz, K., Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004–2014. *J. Financ. Econom.*, 2015, **14**, 81–127.

Domenico, M.D., Solèribalta, A., Cozzo, E., Kivel, M. and Moreno, Y., Mathematical formulation of multi-layer networks. *Physic. Rev. X*, 2013, **3**, 041022.

Fang, L., Sun, B., Li, H. and Yu, H., Systemic risk network of Chinese financial institutions. *Emerg. Mark. Rev.*, 2018, **35**, 190–206.

Gallotti, R. and Barthelemy, M., The multilayer temporal network of public transport in Great Britain. *Sci. Data.*, 2015, **2**, 140056.

Hansen, P.R. and Lunde, A., Does anything beat a GARCH(1, 1)? A comparison based on test for superior predictive ability. 2003 IEEE International Conference on Computational Intelligence for Financial Engineering, Hong Kong, China, 20–23 March, 2003.

Härdle, W.K., Wang, W. and Yu, L., TENET:tail-Event driven NETwork risk. *J. Econom.*, 2016, **192**, 499–513.

Hautsch, N., Schaumburg, J. and Schienle, M., Forecasting systemic impact in financial networks. *Int. J. Forecast.*, 2014, **30**, 781–794.

Hautsch, N., Schaumburg, J. and Schienle, M., Financial network systemic risk contributions. *Rev. Financ.*, 2015, **19**, 685–738.

Hoff, P.D., Multilinear tensor regression for longitudinal relational data. *Ann. Appl. Stat.*, 2015, **9**, 1169.

Hoff, P.D., Raftery, A.E. and Handcock, M.S., Latent space approaches to social network analysis. *J. Am. Stat. Assoc.*, 2002, **97**, 1090–1098.

Holme, P. and Saramäki, J., Temporal networks. *Phys. Rep.*, 2012, **519**, 97–125.

Hong, Y., A test for volatility spillover with application to exchange rates. *J. Econom.*, 2001, **103**, 183–224.

Hong, Y., Liu, Y. and Wang, S., Granger causality in risk and detection of extreme risk spillover between financial markets. *J. Econom.*, 2009, **150**, 271–287.

Huang, X., Zhou, H. and Zhu, H., A framework for assessing the systemic risk of major financial institutions. *J. Bank. Financ.*, 2009, **33**, 2036–2049.

Huang, W.Q., Zhuang, X.T., Yao, S. and Uryasev, S., A financial network perspective of financial institutions' systemic risk contributions. *Physica. A.*, 2016, **456**, 183–196.

Huang, Q., De Haan, J. and Scholtens, B., Analysing systemic sisk in the Chinese banking system. *Pacific Econom. Rev.*, 2019, **24**, 348–372.

Hung, J.C., Deregulation and liberalization of the Chinese stock market and the improvement of market efficiency. *Q. Rev. Econ. Finance.*, 2009, **49**, 843–857.

Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J.P., Moreno, Y. and Porter, M.A., Multilayer networks. *J. Complex. Netw.*, 2014, **2**, 203–271.

Kolar, M., Song, L., Ahmed, A. and Xing, E.P., Estimating time-varying networks. *Ann. Appl. Stat.*, 2010, **4**, 94–123.

Kostakos, V., Temporal graphs. *Physica. A.*, 2009, **388**, 1007–1023.

Kritzman, M., Li, Y., Page, S. and Rigobon, R., Principal component as a measure of systemic risk. *J. Portf. Manag.*, 2011, **37**, 112–126.

Lacasa, L., Nicosia, V. and Latora, V., Network structure of multivariate time series. *Sci. Rep.*, 2015, **5**, 15508.

Langfield, S., Liu, Z. and Ota, T., Mapping the UK interbank system. *J. Bank. Financ.*, 2014, **45**, 288–303.

Levy-Carciente, S., Kenett, D.Y., Avakian, A., Stanley, H.E. and Havlin, S., Dynamical macroprudential stress testing using network theory. *J. Bank. Financ.*, 2015, **59**, 164–181.

Li, S. and Wen, S., Multiplex networks of the guarantee market: Evidence from China. *Complexity*, 2017, **2017**, 9781890.

Li, H., Hong, Y. and Wang, S., Information spillover among China's A-shares market, US stock market and HK stock market. *Econom. Res. J.*, 2011, **37**, 15–25. (in Chinese).

Liu, X., Cheng, S., Wang, S., Hong, Y. and Li, Y., An empirical study on information spillover effects between the Chinese copper futures market and spot market. *Physica. A.*, 2008, **387**, 899–914.

Mazzarisi, P., Zaoli, S., Lillo, F., Delgado, L. and Gurtner, G., New centrality and causality metrics assessing air traffic network interactions. *J. Air Trans. Manag.*, 2020, **85**, 101801.

Molina-Borboa, J.L., Martínez-Jaramillo, S., López-Gallo, F. and van der Leij, M., A multiplex network analysis of the Mexican banking system: Link persistence, overlap and waiting times. *J. Netw. Theory Finance*, 2015, **1**, 99–138.

Musmeci, N., Nicosia, V., Aste, T., Di Matteo, T. and Latora, V., The multiplex dependency structure of financial markets. *Complexity*, 2017, **2017**, 9586064.

Patro, D.K., Qi, M. and Sun, X., A simple indicator of systemic risk. *J. Financ. Stabil.*, 2013, **9**, 105–116.

Poledna, S., Molina-Borboa, J.L., Martínez-Jaramillo, S., van der Leij, M. and Thurner, S., The multi-layer network nature of systemic risk and its implications for the costs of financial crises. *J. Financ. Stabil.*, 2015, **20**, 70–81.

Tarashev, N.A., Borio, C. and Tsatsaronis, K., Attributing systemic risk to individual institutions. BIS Working Paper No. 308, Bank for International Settlements, 2010.

Tumminello, M., Aste, T., Di Matteo, T. and Mantegna, R.N., A tool for filtering information in complex systems. *Proc. Natl. Acad. Sci. U.S.A.*, 2005, **102**, 10421–10426.

Tumminello, M., Micciche, S., Lillo, F., Piilo, J. and Mantegna, R.N., Statistically validated networks in bipartite complex systems. *PLoS ONE*, 2011, **6**, e17994.

Wang, G.J., Xie, C., He, K. and Stanley, H.E., Extreme risk spillover network: Application to financial institutions. *Quant. Finance*, 2017, **17**, 1417–1433.

Wang, G.J., Jiang, Z.Q., Lin, M., Xie, C. and Stanley, H.E., Interconnectedness and systemic risk of China's financial institutions. *Emerg. Mark. Rev.*, 2018a, **35**, 1–18.

Wang, G.J., Xie, C., Zhao, L. and Jiang, Z.Q., Volatility connectedness in the Chinese banking system: Do state-owned commercial banks contribute more?. *J. Int. Financ. Markets Inst. Money*, 2018b, **57**, 205–230.

Xu, Q., Li, M., Jiang, C. and He, Y., Interconnectedness and systemic risk network of Chinese financial institutions: A LASSO-CoVaR approach. *Physica. A.*, 2019, **534**, 122173.

Yellen, J.L., Interconnectedness and systemic risk: Lessons from the financial crisis and policy implications. Technical report, 2013.

Zhou, C., Are banks too big to fail? Measuring systemic importance of financial institutions. *Inter. J. Central Bank.*, 2010, **6**, 205–250.