Emerging Markets Review 35 (2018) 1–18

Contents lists available at ScienceDirect

Emerging Markets Review

journal homepage: www.elsevier.com/locate/emr

Interconnectedness and systemic risk of China's financial institutions

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A R T I C L E   I N F O

Article history:
Received 27 February 2017
Received in revised form 7 October 2017
Accepted 3 December 2017
Available online 7 December 2017

Jel classification:
G01
G18
G21

Keywords:
Systemic risk
Interconnectedness
Financial crisis
Financial regulation
Financial institutions
CoVaR

A B S T R A C T

We investigate the interconnectedness and systemic risk of China's financial institutions by constructing dynamic tail-event driven networks (TENETs) at 1% risk level based on weekly returns of 24 publicly-listed financial institutions from 2008 to 2016. Total connectedness reaches a peak when the system exhibits stress, especially during the recent period from mid-2014 to end-2016. Large commercial banks and insurers usually exhibit systemic importance, but some small firms are systemically important due to their high level of incoming (outgoing) connectedness. Our results provide useful information to regulators when they assess systemic risk of financial institutions and formulate macroprudential supervision policy.

1. Introduction

The recent global financial crisis greatly affected the worldwide economy and financial system and revealed significant flaws in the existing financial regulatory system. Identifying and supervising systemically important financial institutions (SIFIs) has become an urgent task for financial regulators in the post-crisis era. One of the distinguishing features of the financial system is the interconnectedness among financial agents (e.g., market participants and institutions) (Yellen, 2013). This interconnectedness introduces diversification, which can reduce risk and improve financial stability, but it also introduces systemic risk because an individual event (e.g., the failure of a highly interconnected institution such as Lehman Brothers) can turn into a systemic event and endanger overall financial stability. Thus academics have proposed that a financial institution can be "too interconnected to fail" (Markose et al., 2012; Gofman, 2017), and the Financial Stability Board (FSB) established after the 2009

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https://doi.org/10.1016/j.ememar.2017.12.001

G20 London summit uses the interconnectedness among financial institutions as an important indicator for identifying global systemically important banks (G-SIBs).[1] Accordingly, researchers have focused their attention on how to measure systemic risk of financial institutions by considering the interconnectedness.

Although the recent global financial crisis caused a worldwide recession, China's economic growth has been persistent, rapid, and central to global economic growth since China joined the WTO in 2001. For example, in 2016 China's GDP grew 6.7% and contributed nearly 39% to global economic growth. During the past two decades, China's financial system also has rapidly developed and played an important role in fueling the economic expansion of China. In the list of G-SIBs since 2011 and the list of global systemically important insurers (G-SIIs) since 2014, five of China's financial instructions — the Agricultural Bank of China (ABC), the Bank of China (BOC), the China Construction Bank (CCB), the Industrial and Commercial Bank of China Ltd. (ICBC), and the Ping An Insurance (Group) Co. of China, Ltd. (PAI) — have been among them.[2] This means that China also faces regulatory challenges to its financial institutions. In response to the global financial crisis, the Chinese government and regulators have attempted to build a countercyclical macroprudential policy framework.[3] The major goal of macroprudential supervision is measuring systemic risk contribution of financial institutions. Thus, our goal here is to study systemic risk of China's financial institutions using a network interconnectedness approach.

Based on such publicly available market data as equity prices and the spread of credit default swaps (CDS), many market-based methods have been proposed to measure the interconnectedness and systemic risk among financial institutions (see, a review by Bisias et al., 2012), and these approaches can be broadly split into three groups.[4] The first uses correlations across financial assets to estimate the default probabilities of financial institutions. Representative methods include the cross-correlation coefficient (Huang et al., 2009; Patro et al., 2013) and the principal component analysis (PCA) (Kritzman et al., 2011; Billio et al., 2012). The second group measures financial institutions' spillover effects and systemic risk contributions using tail-dependence across financial institutions. For example, Zhou (2010) proposes two measures, systemic impact index (SII) and vulnerability index (VI), for identifying the systemic importance of financial institutions using the multivariate extreme value theory. Adrian and Brunnermeier (2016) develop the conditional value-at-risk (CoVaR), defined as the VaR of the financial system when some specific event affects a single institution. Accordingly, they propose a systemic risk measure, ΔCoVaR, defined as the difference between CoVaRs when a financial institution is and is not under distress. Acharya et al. (2017) present two systemic risk measures, marginal expected shortfall (MES) and systemic expected shortfall (SES), where the former is defined as a financial institution's losses when the entire financial system is experiencing losses, and the latter is calculated by taking into account the financial institution's MES and its leverage. By considering the financial institution's size and leverage, Acharya et al. (2012) and Brownlees and Engle (2017) extend MES to SRISK, which can quantify the effect of a systemic event on a financial institution's capital shortfall. Banulescu and Dumitrescu (2015) extend MES to another systemic risk metric, the component expected shortfall (CES), which is related to a financial institution's MES and its relative market capitalization. Both the above two groups of systemic risk measurements focus on local interdependence among financial institutions (especially the interaction between a financial institution and the financial system) and ignore the network interconnectedness among the financial institutions from a systemic perspective. These approaches thus may underestimate systemic risk contribution of highly interconnected financial institutions because they cannot capture risk spillovers found in the topology of financial networks (Hautsch et al., 2015). Thus, the third group of approaches uses network theory to measure interconnectedness among financial agents in order to quantify the systemic risk. Network theory has been a powerful tool for analyzing the complex financial system because it can abstract the financial system to a financial network with a set of nodes and edges, revealing the underlying structure and complexity of the system (Levy-Carciente et al., 2015; Battiston et al., 2016). For example, Billio et al. (2012) propose a Granger-causality network (also known as a mean-spillover network) to study the interconnectedness and systemic risk among hedge funds, brokers, banks, and insurers. Diebold and Yılmaz (2014) present a volatility spillover network based on variance decompositions, which is a weighted and directed network for quantifying the interconnectedness of financial firms. Hautsch et al. (2015) design a systemic risk measure, the realized systemic risk beta, which is based on their proposed tail risk interdependence network. Wang et al. (2017) propose an extreme risk spillover network based on the Granger-causality risk test for investigating the interconnectedness of financial firms. Using a single-index quantile regression augmented with non-linearity and variable selection, Härdle et al. (2016) extend CoVaR to a tail-event driven network (TENET) that can measure the systemic risk contribution of a financial institution by taking into account its tail interconnectedness with other relevant financial institutions. There are two main differences between the TENET of Härdle et al. (2016) and the Granger-causality network of Billio et al. (2012): (i) the TENET is a weighted and directed network while the Granger-causality network is an unweighted and directed network and (ii) the TENET is a tail risk interdependence network while the Granger-causality network is a mean-spillover network. Thus the TENET has two advantages: (i) as a weighted network, it includes more information than the Granger-causality network and (ii) it has more power to capture the extreme risk or tail event because extreme risk or tail event is usually reflected in the tails of equity returns.

[1] See the assessment methodology of G-SIBs developed by the Basel Committee on Banking Supervision (BCBS) (http://www.bis.org/publ/bcbs255.pdf).

[2] For details, the BOC is listed in the G-SIBs of 2011–2016, ICBC in the G-SIBs of 2013–2016, ABC in the G-SIBs of 2014–2016, CCB in the G-SIBs of 2015 and 2016, and PAI in the G-SIIs of 2014–2016.

[3] For example, in 2011 Zhou Xiaochuan, the governor of China's central bank, published a paper (in Chinese) discussing the response of financial policy to the financial crisis and the prudential macroeconomic policy framework (see Zhou, 2011).

[4] Note that in Section 5 we discuss the differences between market-based approaches and indicator-based approaches (e.g., the assessment approach of FSB) for measuring systemic risk.

Here, we use the TENET tool of Härdle et al. (2016) to study the interconnectedness and systemic risk of China's financial institutions. Using data from 24 publicly-listed financial institutions (including banks, securities, and insurers) in China from 2008 to 2016, we construct dynamic TENETs and analyze the topological features of dynamic interconnectedness to identify systemically important financial institutions. Our empirical investigation contributes the following.[5]

(i) Because we use network analysis, we amplify the literature on measuring the systemic risk of financial institutions, especially those in China. Although much empirical research has studied the systemic risk to China's financial institutions, it has used such approaches as MES, ΔCoVaR, SRISK (see, e.g., Gang and Qian, 2015; Huang et al., 2017)[6] and ignores the network perspective. Thus, our study using TENETs complements the existing literature.
(ii) Because the three G-SIBs (ICBC, BOC, and CCB) and one G-SII (PAI) released by FSB are identified as both systemic risk receivers (SRRs) and systemic risk emitters (SREs), our empirical study is an asset for regulators. We find that several small firms are systemically important due to their high level of incoming or outgoing connectedness. Thus, regulators should not limit their attention to such large financial institutions as ICBC, BOC, and CCB, but also focus on hub nodes in the network with a high level of tail connectedness.
(iii) We find that both the total connectedness (TC) and the cross-sectoral connectedness of dynamic TENETs reach a peak when the stability of the system is uncertain or the system exhibits distress. This information allows regulators to use the TC as an early-warning indicator for system distress. An increase in the cross-sectoral connectedness caused the high TC level in the recent bullish period and subsequent turbulence in the 2015–2016 Chinese stock market. This indicates that the three regulatory commissions, i.e., the China Banking Regulatory Commission (CBRC), the China Securities Regulatory Commission (CSRC), and the China Insurance Regulatory Commission (CIRC), should focus on the cross-sectoral connectedness and increase the coordination of their supervisory responsibilities.

In Section 2 of what follows, we describe the CoVaR and TENET methods and introduce some connectivity measures. We show the data in Section 3, the empirical results in Section 4, and present our discussion in Section 5 and conclusions in Section 6.

2. Methodology

The TENET of Härdle et al. (2016) is based on the CoVaR of Adrian and Brunnermeier (2016) and is calculated using a semiparametric quantile regression framework that takes into consideration non-linearity and variable selection. We thus first introduce the concept of CoVaR and then present TENET, including the three steps for measuring systemic risk, and finally describe some connectivity measures for quantifying the network's topological properties.

2.1. CoVaR

A widely-used measure, value-at-risk (VaR), assesses the riskiness of a financial institution. Given the return (loss) $X_{i,t}$ of financial institution i at time t and the quantile level $\tau \in (0,1)$, $\mathrm{VaR}_{i,t,\tau}$ is defined as the τ-quantile of the return distribution

$$\Pr\left(X_{i,t} \leq \mathrm{VaR}_{i,t,\tau}\right) \equiv \tau. \tag{1}$$

Adrian and Brunnermeier (2016) define $\mathrm{CoVaR}_{j|C(X_{i,t}),t,\tau}$ as the VaR of financial institution j conditional on some event $C(X_{i,t})$ of financial institution i at time t, which is the τ-quantile of the conditional probability distribution

$$\Pr\left(X_{j,t}|C\left(X_{i,t}\right) \leq \mathrm{CoVaR}_{j|C\left(X_{i,t}\right),t,\tau}\right) \equiv \tau, \tag{2}$$

where the information set $C(X_{i,t})$ includes some event of $X_{i,t}=\mathrm{VaR}_{i,t,\tau}$ and M_{t-1} that is a vector of macroeconomic state variables. For simplicity, we designate $\mathrm{CoVaR}_{j|C(X_{i,t}),t,\tau}$ as $\mathrm{CoVaR}_{j|i,t,\tau}$ by simplifying the subscript $C(X_{i,t})$ to i.

Adrian and Brunnermeier (2016) propose the use of linear quantile regression for estimating the time-variation VaR and CoVaR, i.e.,

$$X_{i,t} = \alpha_i + \gamma_i M_{t-1} + \varepsilon_{i,t}, \tag{3}$$

$$X_{j,t} = \alpha_{j|i} + \gamma_{j|i} M_{t-1} + \beta_{j|i} X_{i,t} + \varepsilon_{j|i,t}. \tag{4}$$

[5] For more discussion on our contributions, see Section 5.
[6] Note that most of relevant works are published in the Chinese journals, to name a few, see Fan et al. (2011), Liang et al. (2013), Lu and Hu (2014), and Bu and Li (2015).

Then, $\mathrm{VaR}_{i,t,\tau}$ and $\mathrm{CoVaR}_{j|i,t,\tau}$ of financial institutions i and j at time t can be estimated using the predicted values from the above regressions, i.e.,

$$\widehat{\mathrm{VaR}}_{i,t,\tau} = \hat{\alpha}_i + \hat{\gamma}_i M_{t-1}, \tag{5}$$

$$\widehat{\mathrm{CoVaR}}_{j|i,t,\tau} = \hat{\alpha}_{j|i} + \hat{\gamma}_{j|i} M_{t-1} + \hat{\beta}_{j|i} \widehat{\mathrm{VaR}}_{i,t,\tau}, \tag{6}$$

where $\hat{\beta}_{j|i}$ reflects the level of tail-event interconnectedness from institution i to institution j.

2.2. TENET

When estimating CoVaR, Adrian and Brunnermeier (2016) consider the interaction between two financial institutions in an isolated environment, only do pairwise quantile regression, and ignore all other possible interaction effects in a system. This is important because the two interacting financial institutions may also be affected by or interact with other financial institutions (Wang et al., 2016). Thus, Härdle et al. (2016) extend the bivariate model of Adrian and Brunnermeier (2016) to a high-dimensional context by using a variable selection approach to consider more variables. Adrian and Brunnermeier (2016) assume there is a linear dependency between two financial institutions, but earlier research such as that of Chao et al. (2015) finds that there is a non-linear dependency between any pair of financial assets, especially when the economic situation is uncertain. Thus, Härdle et al. (2016) propose a TENET based on single-index quantile regressions that account for non-linearity and variable selection in a high dimensional variable setting. The first step of TENET is to estimate each financial institution's VaR using Eqs. (3) and (5). Using single-index quantile regressions, the second step is to construct a risk interdependence network. Accordingly, we have[7]

$$X_{j,t} = g\left(\beta_{j|R_j}^{\mathrm{T}} R_{j,t}\right) + \varepsilon_{j,t}, \tag{7}$$

$$\widehat{\mathrm{CoVaR}}_{j|\tilde{R}_j,t,\tau}^{\mathrm{TENET}} \equiv \hat{g}\left(\hat{\beta}_{j|\tilde{R}_j}^{\mathrm{T}} \tilde{R}_{j,t}\right), \tag{8}$$

$$\hat{D}_{j|\tilde{R}_j} \equiv \frac{\partial \hat{g}\left(\hat{\beta}_{j|\tilde{R}_j}^{\mathrm{T}} R_{j,t}\right)}{\partial R_{j,t}}\Big|_{R_{j,t}=\tilde{R}_{j,t}} = \hat{g}'\left(\hat{\beta}_{j|\tilde{R}_j}^{\mathrm{T}} \tilde{R}_{j,t}\right) \hat{\beta}_{j|\tilde{R}_j}, \tag{9}$$

where $R_{j,t} = \{X_{-j,t}, M_{t-1}, B_{j,t-1}\}$ is the information set that includes:

(i) $X_{-j,t} = \{X_{1,t}, X_{2,t}, \ldots, X_{N,t}\}$, which is the set of $N-1$ explanatory variables, i.e., the returns of all financial institutions except financial institution j, and N is the number of financial institutions;
(ii) M_{t-1}, which is a vector of macroeconomic state variables at time $t-1$; and
(iii) $B_{j,t-1}$, which is a vector of firm characteristics at time $t-1$, calculated by the balance sheet information of financial institution j.

Thus, the parameters $\hat{\beta}_{j|\tilde{R}_j}$ also consist of three parts, i.e., $\beta_{j|\tilde{R}_j} = \left\{\beta_{j|-j}, \quad \beta_{j|M}, \quad \beta_{j|B_j}\right\}^{\mathrm{T}}$. $\tilde{R}_{j,t}$ is a set including $\widehat{\mathrm{VaR}}_{-j,t,\tau}$, M_{t-1}, and $B_{j,t-1}$, i.e., $\tilde{R}_{j,t} = \left\{\widehat{\mathrm{VaR}}_{-j,t,\tau}, M_{t-1}, B_{j,t-1}\right\}$, where $\widehat{\mathrm{VaR}}_{-j,t,\tau}$ is a set of the estimated VaRs of all financial institutions except for financial institution j. $\hat{\beta}_{j|\tilde{R}_j}$ is a set of estimated parameters of $\beta_{j|\tilde{R}_j}$, i.e., $\hat{\beta}_{j|\tilde{R}_j} = \left\{\hat{\beta}_{j|-j}, \hat{\beta}_{j|M}, \hat{\beta}_{j|B_j}\right\}^{\mathrm{T}}$. In Eq. (8), $\widehat{\mathrm{CoVaR}}_{j|\tilde{R}_j,t,\tau}^{\mathrm{TENET}}$ is the TENET risk that includes the influences of all other financial institutions on financial institution j and the non-linearity that is reflected in the shape of a link function $g(\cdot)$. $\hat{D}_{j|\tilde{R}_j}$ is the gradient that quantifies the marginal effect of covariates, and it also includes three parts, i.e., $\hat{D}_{j|\tilde{R}_j} = \left\{\hat{D}_{j|-j}, \quad \hat{D}_{j|M}, \quad \hat{D}_{j|B_j}\right\}^{\mathrm{T}}$. $\hat{D}_{j|-j}$ measures spillover effects from all other financial institutions to financial institution j, and its componentwise expression is $\hat{D}_{j|-j} = \left\{\hat{D}_{j|i} | 1 \le i \le N, i \ne j\right\}$, where $\hat{D}_{j|i}$ is the influence (or the tail interconnectedness) from financial institution i to financial institution j. Thus, we obtain a weighted adjacency matrix for the tail-event driven network (TENET) with a set of nodes and directed edges. Let $G(V, E)$ be the TENET, where $V = \{1, 2, \ldots, N\}$ is a set of nodes (institutions) and E the set of directed edges across nodes. We define the weighted adjacency matrix A of TENET to be

$$A = \left(|\hat{D}_{j|i}|\right)_{N \times N}, \tag{10}$$

[7] For a detailed introduction of TENET, see Härdle et al. (2016).

where $|\hat{D}_{j|i}|$ is the absolute value of $\hat{D}_{j|i}$ and is zero when $j = i$, which allows us to measure the level of tail risk spillover from financial institution i to financial institution j. Härdle et al. (2016) use rolling windows to estimate time-varying VaRs and build dynamic TENETs. We split the sample data for financial institutions during the investigated period among W windows (w=1,2,…, W) of size S. The TENET at window w is denoted as $G_w(V, E_w)$ and its weighted adjacency matrix as A_w.

As in Billio et al. (2012), Diebold and Yılmaz (2014), and Hautsch et al. (2015), we mainly use stock-return (tail) interconnections to generate the network structure of financial institutions. A tail risk connection from one institution to another in the TENET represents their contagion or spillover effect, but its economic interpretation cannot be empirically detected by the available market data because the most relevant data such as institutions' credit and liquidity exposures are business confidential and publicly unavailable (Hautsch et al., 2015). By introducing such control variables as firm characteristics and macroeconomic state variables in the CoVaR and TENET approaches, we exclude several common risk factors such as market risk in the tail risk connections. Thus, the identified tail risk connections mainly spring from direct credit or liquidity exposure between financial institutions, sector risk, and exposure on common customers due to the same business model.

In the third step of TENET, Härdle et al. (2016) propose two systemic risk indices, the systemic risk receiver (SRR) index and the systemic risk emitter (SRE) index, for measuring SIFIs. These two indices connect "too interconnected to fail" with "too big to fail" financial institutions by considering both their incoming and outgoing connections and their market capitalization.[8] The SRR and SSE indices for financial institution j at window w are respectively defined as

$$\mathrm{SRR}_{j,w} = \mathrm{MC}_{j,w} \sum_{i \in E^{\mathrm{IN}}_{j,w}} \left(|\hat{D}^{w}_{j|i}| \cdot \mathrm{MC}_{i,w} \right), \tag{11}$$

and

$$\mathrm{SRE}_{j,w} = \mathrm{MC}_{j,w} \sum_{i \in E^{\mathrm{OUT}}_{j,w}} \left(|\hat{D}^{w}_{i|j}| \cdot \mathrm{MC}_{i,w} \right), \tag{12}$$

where $|\hat{D}^{w}_{j|i}|$ $\left(|\hat{D}^{w}_{i|j}|\right)$ is the impact of financial institution j (i) on financial institution i (j) at window w, which represents the incoming (outgoing) tail interconnectedness of financial institution j. $E^{\mathrm{IN}}_{j,w}$ $\left(E^{\mathrm{OUT}}_{j,w}\right)$ is the set of financial institutions linked with financial institution j by incoming (outgoing) edges at window w, and $\mathrm{MC}_{k,w}$ ($k = i,j$) is the market capitalization of financial institution k at the ending date of window w.

2.3. Connectivity measures

Following Wang et al. (2017), we select three categories of connectivity measurements to analyze the topological properties of the network: (i) system-wide connectivity, (ii) institutional-level connectivity, and (iii) sector-conditional connectivity.

We introduce two system-wide connectivity measures, total connectedness and global efficiency. Total connectedness (TC) quantifies the overall level of tail risk spillovers by taking the network as a whole, defined as the sum of $|\hat{D}^{w}_{j|i}|$ for all actual connections at window w,[9] i.e.,

$$\mathrm{TC}_w = \sum_{j=1}^{N} \sum_{i=1, i \neq j}^{N} \left| \hat{D}^{w}_{j|i} \right|. \tag{13}$$

[8] We choose market capitalization as a proxy of firm size because it can capture a firm's dynamic size and indicate the public opinion on a firm's net worth. Moreover, the market capitalization is a market evaluation of a firm's future value and differs from the accounting value of assets and liabilities because it is a forward-looking indicator and may reflect the future factors. The rise and fall of the market capitalization reflects the trading atmosphere in the investment market and the latest valuation of the firm. This choice also follows Brownlees and Engle (2017) and van de Leur et al. (2017) who characterize the firm size using the market capitalization when measuring system risk. Note that we do not take into account the firm's ownership structure that may affect its market capitalization because it is beyond our focus, but this concern deserves to be studied further. For robustness testing, we also use total assets as an alternative measure for firm size in Eqs. (11) and (12). Since the data of total assets for each financial institution are collected from the quarterly balance sheet, we transform the quarterly data into weekly data using cubic spline interpolation. We should keep in mind that this transformation would introduce data estimation error. We find that our results using market capitalization as a measure for firm size cover the obtained information using total assets and contain more other useful information. On another note, our central findings are supported by the SRR and SRE measures using total assets, suggesting that our results to a certain extent are robust in terms of size measure. The results for the SRR and SRE indices of each financial institution in dynamic TENETs using total assets are available from the authors upon request. 0

[9] If TC is normalized by $N(N-1)$, which is the number of all possible edges in a network, it becomes a (weighted) network density (NE) measure used by Billio et al. (2012) and Wang et al. (2017). Here, we focus only on TC, because both TC and NE have the same trend.

Global efficiency (GE) was proposed by Latora and Marchiori (2001), quantifies how efficiently a network exchanges information, and is defined by the average of the inverse shortest path length in the network, i.e.,

$$\mathrm{GE}_w = \frac{1}{N(N-1)} \sum_{j=1}^{N} \sum_{i=1, i \neq j}^{N} \frac{1}{d_{j|i}^w}, \tag{14}$$

where $d_{j|i}^w$ is the shortest path length from institution (node) i to j in a network at window w.[10] When there is no path in the network from i to j, $d_{j|i}^w = +\infty$.

We introduce two directional measures of the sector strength of the sector-conditional connectivity, i.e., the in-strength of the sector and the out-strength of sector, and these are used to measure each sector's incoming and outgoing connectedness, respectively. The in-strength of sector m (ISS) is the sum of the weights of incoming edges connected to institutions belonging to sector m, i.e.,

$$\mathrm{ISS}_m^w = \sum_{j \in V_m} \sum_{i=1}^{N} \left| \hat{D}_{j|i}^w \right|. \tag{15}$$

The out-strength of sector m (OSS) is the sum of weights of outgoing edges connected to institutions belonging to sector m, i.e.,

$$\mathrm{OSS}_m^w = \sum_{i=1}^{N} \sum_{j \in V_m} \left| \hat{D}_{i|j}^w \right|. \tag{16}$$

In Eqs. (15) and (16), V_m is the set of institutions belonging to sector m, where $m = 1$, 2, and 3 correspond to the three investigated sectors, i.e., banks, securities, and insurers, and $V = \{V_1, V_2, V_3\}$. To investigate the strength of tail risk spillover effects from one sector m to another sector n or to itself, we introduce another sector-conditional connectivity measure, the strength of cross sector (SCS), which is defined

$$\mathrm{SCS}_{n|m}^w = \frac{1}{N_n N_m} \sum_{i \in V_n} \sum_{j \in V_m} \left| \hat{D}_{i|j}^w \right| \tag{17}$$

where N_n and N_m are the number of institutions belonging to sectors n and m, respectively. When calculating the strength from sector m to itself, in Eq. (17) $N_n = N_m - 1$, $V_n = V_m$, and $i \neq j$.

For institution-level connectivity, we introduce two directional measures of institution strength, i.e., the in-strength of the institution and the out-strength of the institution, which allow us to measure each institution's incoming and outgoing connectedness, respectively. The in-strength of institution j (ISI) is the sum of weights $\left(\left|\hat{D}_{j|i}^w\right|\right)$ of incoming edges from other institutions to institution j in the network at window w, i.e.,

$$\mathrm{ISI}_j^w = \sum_{i=1, i \neq j}^{N} \left| \hat{D}_{j|i}^w \right|. \tag{18}$$

The out-strength of institution j (OSI) is the sum of weights $\left(\left|\hat{D}_{i|j}^w\right|\right)$ of outgoing edges from institution j to other institutions, i.e.,

$$\mathrm{OSI}_j^w = \sum_{i=1, i \neq j}^{N} \left| \hat{D}_{i|j}^w \right|. \tag{19}$$

3. Data

We apply TENET to publicly listed financial institutions in China for analyzing their interconnectedness and systemic risk. Our data comprise 24 publicly listed financial institutions in China during the period from 4 January 2008 to 30 December 2016. We select the 2008 beginning date because several important financial institutions (e.g., the China Construction Bank, the China CITIC Bank, Industrial Bank, the Bank of Beijing, the Bank of Nanjing, and the Bank of Ningbo) were not listed on China's A-share market until 2007. We select 24 financial institutions in our sample following two constraints (i) the financial institution

[10] In the TENET, the shortest path length from institution i to j means that a shock of i (i.e., its equity price fluctuation) spilling over to j needs how many other institutions to act as intermediaries. For details, see Billio et al. (2012) who describe the shortest path measure when introducing the closeness measure.

Table 1
Descriptive statistics of weekly returns of 24 publicly listed financial institutions in China during the period of 2008–2016. Notes: This table shows 24 publicly listed financial institutions in China and their abbreviations in numerical order according their ticker codes within three sectors. In the ticker code, ".SZ" or ".SH" means that the firm's stock is traded on the Shenzhen Stock Exchange or the Shanghai Stock Exchange. All the Jarque-Bera statistics are significant at the 1% level, which reject the null hypothesis of Gaussian distribution for the returns.

Ticker code	Financial institution	Abbr.	Mean	Maximum	Minimum	Std. Dev.	Jarque-Bera
Panel A: Banks							
000001.SZ	Ping An Bank	PAB	−0.0031	0.2225	−0.5246	0.0650	2636.271
002142.SZ	Bank of Ningbo	NBCB	−0.0006	0.2170	−0.2905	0.0538	220.7804
600000.SH	Shanghai Pudong Development Bank	SPDB	−0.0026	0.2187	−0.3935	0.0605	962.1555
600015.SH	Huaxia Bank	HXB	−0.0013	0.2095	−0.3365	0.0554	336.6739
600016.SH	China Minsheng Banking Corp., Ltd.	CMBC	−0.0011	0.2152	−0.2834	0.0523	466.8645
600036.SH	China Merchants Bank	CMB	−0.0017	0.1579	−0.2415	0.0498	106.5210
601009.SH	Bank of Nanjing	NJBK	−0.0013	0.1750	−0.6294	0.0575	19,282.96
601166.SH	Industrial Bank	CIB	−0.0025	0.1978	−0.6575	0.0679	10,527.92
601169.SH	Bank of Beijing	BOB	−0.0017	0.1990	−0.2705	0.0504	280.9081
601328.SH	Bank of Communications	BOCOM	−0.0021	0.1868	−0.2074	0.0483	135.9020
601398.SH	Industrial and Commercial Bank of China Ltd.	ICBC	−0.0013	0.1572	−0.1462	0.0357	212.8555
601939.SH	China Construction Bank	CCB	−0.0013	0.1929	−0.1405	0.0403	188.9955
601988.SH	Bank of China	BOC	−0.0014	0.2150	−0.1628	0.0377	326.2409
601998.SH	China CITIC Bank	CNCB	−0.0010	0.2891	−0.1921	0.0517	329.7216
Panel B: Securities							
000686.SZ	Northeast Securities	NESC	−0.0031	0.3503	−0.7389	0.0821	4371.845
000728.SZ	Guoyuan Securities	GYSC	−0.0017	0.4121	−0.2367	0.0715	268.2221
000783.SZ	Changjiang Securities	CJSC	−0.0029	0.3273	−0.7580	0.0807	5934.358
600030.SH	CITIC Securities	CITICS	−0.0037	0.3255	−0.4173	0.0709	876.8093
600109.SH	Sinolink Securities	SLSC	−0.0036	0.3814	−0.7276	0.0882	4804.728
600837.SH	Haitong Securities	HTSEC	−0.0027	0.3333	−0.8821	0.0816	18,945.82
601099.SH	Pacific Securities	PSC	−0.0046	0.4368	−0.4014	0.0739	1036.749
Panel C: Insurers							
601318.SH	Ping An Insurance (Group) Co. of China, Ltd.	PAI	−0.0023	0.1931	−0.8821	0.0666	83,396.99
601601.SH	China Pacific Insurance (Group) Co., Ltd.	CPIC	−0.0012	0.1818	−0.2120	0.0547	15.53332
601628.SH	China Life Insurance (Group) Co., Ltd.	CLI	−0.0019	0.2719	−0.2425	0.0561	268.3861

should be listed prior to 2008,[11] and (ii) they have no long suspension period.[12] Our sample includes 14 banks, seven securities, and three insurers.[13] Table 1 shows each financial institution's detailed information including its ticker code, full name, and corresponding abbreviation. Following Härdle et al. (2016), we collect weekly closing prices and market capitalization of the 24 financial institutions, available from Wind Info. As mentioned in Section 2, our study focuses on the weekly returns of each financial institution, which are defined as $X_{i,t} = ln(P_{i,t}/P_{i,t-1})$, where $P_{i,t}$ is the closing price of financial institution i on week t. Table 1 also shows summary statistics of the weekly returns of the 24 financial institutions during the investigated period. Note that the mean return value for each institution is negative. The absolute minimum of returns of each financial institution, with exception of four banks (ICBC, CCB, BOC, and CNBC) and one insurer (CLI), is larger than the maximum, suggesting that there is more extreme risk in the left tail of the return distribution. The Jarque-Bera statistic for each institution is significant at the 1% level, which rejects the null-hypothesis of a Gaussian distribution for the returns. Thus, we estimate the VaRs and CoVaRs of the financial institutions using quantile regressions because they do not require us to assume the distribution of returns.

Following Adrian and Brunnermeier (2016) and Härdle et al. (2016), we use balance sheet information[14] to calculate four firm characteristics:

(i) *Leverage*, defined as the ratio of total assets to total equity, i.e., the ratio of the book value of assets (MVA) to the book value of equity (BVE).

[11] For example, the Agricultural Bank of China (ABC), one of the five largest commercial banks in China, is not included in our sample because it was not listed on China's A-share market until 15 July 2010. The five largest commercial banks in China are ICBC, CCB, BOC, ABC, and the Bank of Communication (BOCOM). We rank the order of their market capitalization as of December 2016.

[12] For example, Southwest Securities (SWSC) is not included in the sample because it had a long suspension period beginning from 1 March 2011 until 15 August 2011.

[13] Why does our sample only includes 24 Chinese financial institutions, i.e., 14 banks, seven securities, and three insurers, during the investigated period from 2008 to 2016? As of end-2015, there were (i) 16 banks listed on China's A-share market (similarly hereinafter), where two of them were not listed until mid-2010, (ii) 23 securities, where 14 of them were listed after August 2009, i.e., two/three/three/one/one/four of them were listed in 2009/2010/2011/2012/2014/2015, and (iii) four insurers, where one of them (i.e., the New China Life Insurance Co., Ltd.) was listed on 15 December 2011. In the remaining 9 securities that were listed prior to 2008, two firms including the Guangfa Securities (GFSC) and the Southwest Securities (SWSC) suspended trading for 519 business days and 116 business days during the sample period, respectively. Note that the People's Insurance Co. (Group) of China Ltd. (PICC), one of the big five insurers in China, is not included in our sample because it was listed on the Stock Exchange of Hong Kong on 17 December 2012. Due to the above fact, the number of financial institutions from the three sectors cannot be equal as in Billio et al. (2012) and Härdle et al. (2016).

[14] More precisely, the consolidated balance sheet information.

(ii) *Maturity mismatch*, defined as the ratio of (a) short-term debt minus short-term investments minus cash to (b) total liabilities.
(iii) *Market-to-book*, defined as the ratio of market value of equity (MVE) to BVE.
(iv) *Size*, in which we use the log_{10}BVE as the proxy for firm size.

We collect each financial institution's quarterly balance sheet information from the China Stock Market & Accounting Research (CSMAR) database. We follow Härdle et al. (2016) and transform the quarterly indicators into weekly data using cubic spline interpolation.

As in Adrian and Brunnermeier (2016) and Härdle et al. (2016), we use the seven macro state variables to reflect the general state of the economy:

(i) The *short-term liquidity spread*, defined as the difference between the three-month Shanghai interbank offered rate (3M SHIBOR) and the three-month Treasury bond yield.[15]
(ii) The *change in the three-month Treasury bond yield*.
(iii) The *change in the slope of the yield curve*, which is the spread between the ten-year Treasury bond yield and the three-month Treasury bond yield.
(iv) The *change in the credit spread* between the ten-year ChinaBond's AAA-rated corporate bond yield and the ten-year Treasury bond yield.
(v) The weekly *market returns*, calculated from the CSI 300 Index.[16]
(vi) The *market volatility*, defined as the conditional variances of the CSI 300 Index returns estimated using the GARCH(1,1) model.[17]
(vii) The weekly *real estate sector returns*, computed from the CSI 300 Real Estate Index.

We obtained the weekly data for calculating the seven macro state variables from Wind Info. For each return series, firm characteristic, and macro state variable, there are 460 weekly observations during the investigated period.

4. Empirical results

When computing VaRs and CoVaRs in the TENET analysis, we set the quantile level at $\tau = 0.01$ and the rolling window size at $S = 51$, which corresponds to one year of weekly trading data. We also set the quantile level at $\tau = 0.05$, as in Härdle et al. (2016), but find that the network interconnectedness among the 24 Chinese financial institutions is weak because the network has only a few edges and the elements in the network adjacency matrix are sparse. This suggests that tail-risk spillovers are more likely during extreme events and confirms that co-movement effects and the "herd behaviors" usually occur during systemic events or more extreme conditions of risk. Thus, we focus our attention on dynamic TENETs at the 1% risk level (i.e., at $\tau = 0.01$).

Fig. 1 shows the evolution of the total connectedness (TC) and global efficiency (GE) of dynamic TENETs from 2009 to 2016. An overview of the TC shown in Fig. 1 reveals some interesting patterns. Particularly, it has three prominent circles with high TC values and two trends. The first circle began in mid-2009 and ended in Q1 2010, which was in the latter period of the 2008–2009 global financial crisis, and in the beginning of the European sovereign debt crisis. This was immediately followed by a large decreasing trend until mid-2011 when a second circle emerged. This second circle began in mid-2011 and ended in mid-2012. During this time, the July–August-2011 stock market crash across the US, Europe, Asia, and the Middle East occurred. It was also the most severe period of the European sovereign debt crisis. A stable trend with low TC values then began in mid-2012 and ended in mid-2014. During this stable period there was a long bear market in the Chinese stock exchange. The third circle comprises two phases. The first began in mid-2014 and ended in June 2015, which coincided with the bull market in the Chinese stock exchange. The CSI 300 Index increased by 3200 points (approximately 150%) from 2135 on 6 June 2014 to 5335 on 12 June 2015. This frenzied rise had at least two causes, (i) monetary easing and fiscal stimulus[18] and (ii) a dramatic rise in margin trading.[19] During this phase the TC values increased rapidly and even exceeded the level during the global financial crisis, indicating strong tail risk spillovers across these financial institutions. This irrational exuberance became a bubble that popped

[15] We fellow Jin et al. (2014) and use the treasury bond yield as a substitution for the treasury bond interest rate because there is no unified interest rate in China's treasury bonds with various maturities.

[16] The CSI 300 Index is a capitalization-weighted index that comprises the 300 largest Chinese A-share stocks listed on the Shanghai Stock Exchange (SSE) and the Shenzhen Stock Exchange (SZSE).

[17] On 26 June 2015 the Chinese implied volatility index (iVX) that (like the US VIX) measures market volatility was released by the SSE based on the Shanghai 50ETF options. Here we did not take the iVX into account because of its data limitations.

[18] For example, at the end of December 2014 the annualized broad monetary supply (M2) growth rate in China was 12.2% and the newly increased Renminbi (RMB) loans amounted to 9.78 trillion Yuan with an increase of 890 billion Yuan over the previous year. On 21 November 2014 China's central bank cut its benchmark one-year lending rate by 0.4 percentage points from 6.0% to 5.6% and reduced the benchmark one-year deposit rate by 0.25 percentage points from 3.0% to 2.75%. On 28 February 2015, China's central bank cut its benchmark one-year lending and deposit rates by a further 0.25 percentage points. On 11 May 2015 a further 0.25 percentage points was cut from the benchmark one-year lending and deposit rates. There were also three cuts to the reserve requirement ratio accumulated by 2 percentage points in the first half of 2015.

[19] Margin trading includes two parts, finance transactions and securities lending. During the period from 6 June 2014 to 12 June 2015 the balance of China's securities margin trading increased by 472% from 0.39 trillion Yuan to 2.23 trillion Yuan.

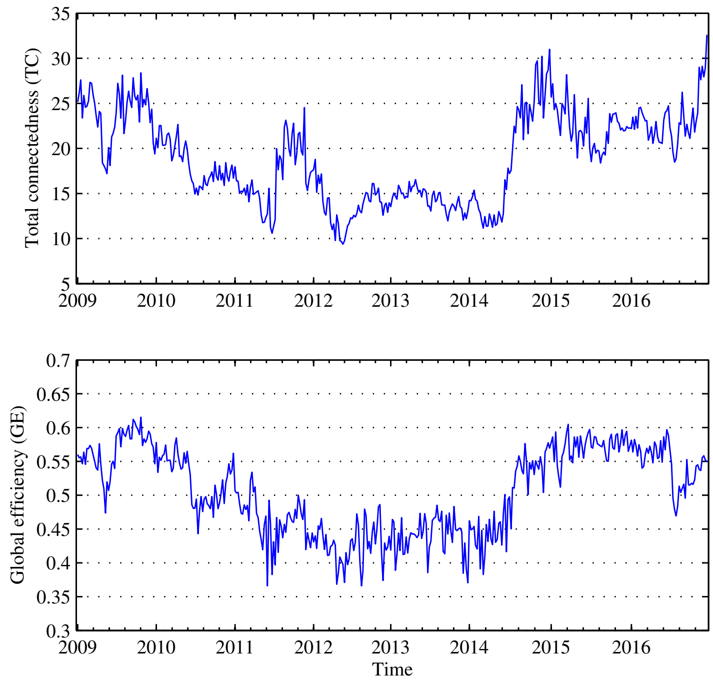

Fig. 1. Total connectedness (TC) and global efficiency (GE) of dynamic TENETs at the 1% risk level for 24 Chinese financial institutions. Notes for this and following figures: The number of windows $W = 409$, window size $S = 51$, and the quantile level $\tau = 0.01$.

during the second phase beginning in June 2015 and ending in mid-2016, during which the "2015–2016 Chinese stock market turbulence" occurred. During this turbulence the CSI 300 Index fell by 42% from 5353 points on 12 June 2015 to 3062 points on 27 May 2016. During this second phase the TC values varied between 20 and 25, which were lower than those during the global financial crisis but greater than those during the European sovereign debt crisis. Although the patterns of the GE are somewhat similar to those of the TC and include a high stage with a falling trend, a stable stage with low GE values, and an increasing trend to a high stage, they differ from TC patterns in two ways: (i) the second circle of the TC does not appear in the GE, and (ii) the GE in the third circle of the TC has a high, stable level except during the earlier increasing trend. In addition, during the period beginning in mid-2016 the TC values are larger than those in the third circle and the GE values are less than those in the third circle. This difference suggests that the increase in the TC only occurs in a few edges, and that the global information exchange efficiency of the network decreases. But we should be wary of the recent upward trend in both the TC and GE values.

Fig. 2 shows the evolution of in-strength of (each) sector (ISS) and out-strength of (each) sector (OSS) in dynamic TENETs. Note that the TC is equal to the sum of the in-strength or out-strength values of all sectors, i.e., $\mathrm{TC}_w = \sum_{m=1}^{3} \mathrm{ISS}_m^w = \sum_{m=1}^{3} \mathrm{OSS}_m^w$, which means that the total connectedness is composed of incoming connectedness or outgoing connectedness of three sectors. Thus, we can analyze the interconnectedness from a directional and sectoral perspective. Because the sample sizes for the three sectors are different, here our analysis mainly focuses on the trends and patterns of incoming connectedness and outgoing connectedness of three sectors. We should keep in mind that the sample size bias may affect the strength of incoming and outgoing connectedness of three sectors. Fig. 2 shows that the trends and patterns of the TC can be tracked by the incoming connectedness or outgoing connectedness of three sectors. The TC in the first circle and the following period with a decreasing

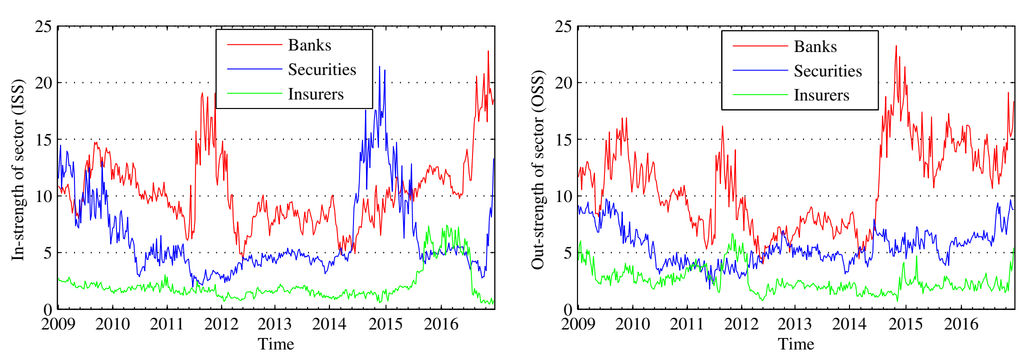

Fig. 2. In-strength of (each) sector (ISS) and out-strength of (each) sector (OSS) in dynamic TENETs at the 1% risk level for 24 Chinese financial institutions. ISS (OSS) measures the level of the incoming (outgoing) connectedness of a sector.

trend is caused by the incoming connectedness of banks and securities. The TC in the second circle is caused by the incoming connectedness of banks because only the ISS of banks rapidly increases. The TC in the period with a stable trend is caused by the incoming connectedness of the three sectors, and the largest contribution to the TC is from banks, followed by securities and insurers. The TC in the first phase of the third circle is reflected in the incoming connectedness of securities because only the ISS of securities exhibits a significant peak. This finding is not accidental because the bull market in the early third circle is led by securities.[20] The contribution to the TC in the second phase of the third circle is arranged in an order of banks, insurers, and securities. Overall, according to the level of incoming connectedness (i.e., the ISS values) banks have the highest tail risk, followed by securities and insurers (except in the third circle). Fig. 2 shows in the OSS for the three sectors (i) that the trends and patterns of outgoing connectedness are similar to those of incoming connectedness, except that the TC in the whole third circle is caused by the outgoing connectedness of banks, and (ii) that during the entire period, banks always emit the highest tail risk, followed by securities and insurers. On of the reasons for the banking sector having the high level of connectedness is that the Chinese financial system is a bank-centered system. According to the annual reports of the three regulatory commissions (i.e., CBRC, CSRC, and CIRC), at the end of 2015, the total assets of the banking, securities, and insurance sectors were above 199.3 billion Yuan, 6.4 billion Yuan, and 12.3 billion Yuan, respectively, with a ratio of 31:1:2. This means that the size of the banking sector is 16 times that of the insurance sector, or 31 times that of the securities sector. But note that the incoming connectedness of the securities sector in the first phase of the third circle reaches a significant peak, suggesting that the incoming connectedness of the securities sector breaks the sample size bias and really reflecting that the market behavior at that period of time is dominated by the securities sector.

To understand the directional connectedness (tail risk spillover) across sectors, we compare the strength from one sector to another or to itself (i.e., SCS), and we present the results in Fig. 3. Fig. 3 (a) shows that on average most of the tail risk (tail interconnectedness) of banks spills over (links) to themselves, except when it is to securities in the first phase of the third circle and to insurers in the second phase of the third circle. Fig. 3 (b) and (c) show that, as in banks, most of the tail risk (tail interconnectedness) of securities and insurers spills over (connects) to themselves. These findings suggest that inter-sectoral tail risk spillovers are ahead of cross-sectoral tail risk spillovers in China's financial institutions. When a systemic event occurs, however, cross-sector tail risk spillovers may take the lead (e.g., the spillover behavior of banks in the third circle), which increases systemic risk and endangers system stability.

Figs. 4 and 5 show the evolution of the in-strength of (each) institution (ISI) and the out-strength of (each) institution (OSI) in dynamic TENETs, respectively. Both the in-strength and out-strength of each institution vary across time. Most ISI values are less than one, and only a few financial institutions have ISI values that are larger (see Fig. 4), indicating that these few receive the highest tail risk. In the first circle and during the period with a decreasing trend (from 2009 to mid-2011), three securities firms, i.e., CITICS, Haitong Securities (HTSEC), Sinolink Securities (SLSC), and Shanghai Pudong Development Bank (SPDB), had the largest ISI values and are the top recipients of tail risk. In the second circle, which covers the worst period of the European sovereign debt crisis, Industrial Bank (CIB) received the most tail risk. In the third circle, three security companies, i.e., Northeast Securities (NESC), Changjiang Securities (CJSC), SLSC, and Pacific Securities (PSC), received the most tail risk, which supports the evidence that securities triggered the recent bull market. PAI, which is the only Chinese insurance company listed in the G-SIIs,[21] received the most tail risk in the second phase of the third circle, during which the "2015–2016 Chinese stock market turbulence" occurred. In late 2016, the Bank of Nanjing (NJBK) and PSC were the largest recipients of tail risk. The distribution of the OSI differs from that of the ISI and is relatively even (see Fig. 5). In the first circle, for example, although most financial institutions emitted some tail risk, the prominent emitters were SPDB, Huaxia Bank (HXB), CIB, CCB, CJCS, PSC, and three insurance companies. In the second circle, the distribution of the OSI was polarized between two groups: one that included China Minsheng Banking Corp., Ltd. (CMBC), BOC, and China Pacific Insurance (Group) Co., Ltd. (CPIC) that emitted the most tail risk, and one that included most financial institutions that emitted little. In the first phase of the third circle, almost all of the banks, two securities firms including Guoyuan Securities (GYSC) and HTSEC, and China Life Insurance (Group) Co., Ltd. (CLI) had large OSI values and were involved in tail risk spillovers. During the turbulent second phase of the third circle the OSI values of most institutions were reduced and only China CITIC Bank (CNBC) had a large out-strength value, suggesting that the outgoing connectedness of individual institutions (except for CNBC) decreased when the bubble burst. Note, however, that the tail interconnectedness of the financial system remains high. The TC values reached a high level in late 2016, which we attribute to CIB because it is the largest emitter of tail risk. Note that NJBK is the largest receiver of tail risk in late 2016. Thus we further attribute the high level of the TC to tail risk spillovers from CIB to NJBK.

As Härdle et al. (2016) point out, interconnectedness alone cannot explain the systemic influence of a financial institution. We thus investigate each financial institution's systemic risk receiver (SRR) index and systemic risk emitter (SRE) index because these two indices simultaneously take into account both the interconnectedness and the size of financial institutions. Figs. 6 and 7 show the evolution of each institution's SRR and SRE indices in dynamic TENETs, respectively. Overall, three banks, i.e., ICBC, BOC, and CCB, are the top systemic risk receivers and emitters, especially during the period from 2009 to mid-2010 and in the third circle from mid-2014 to mid-2016 (covering the bullish period and the market turbulence). As noted in Section 1, these three top systemic risk receivers and emitters are in the G-SIBs lists released by FSB since 2011. In addition to these three

[20] For example, the equity price of CITIC Securities (CITICS) increased 124.32% and hit the 10% daily up-limit four times during the period from 21 November 2014 to 17 December 2014.

[21] Note that the G-SIIs list of 2014–2016 only includes nine insurers.

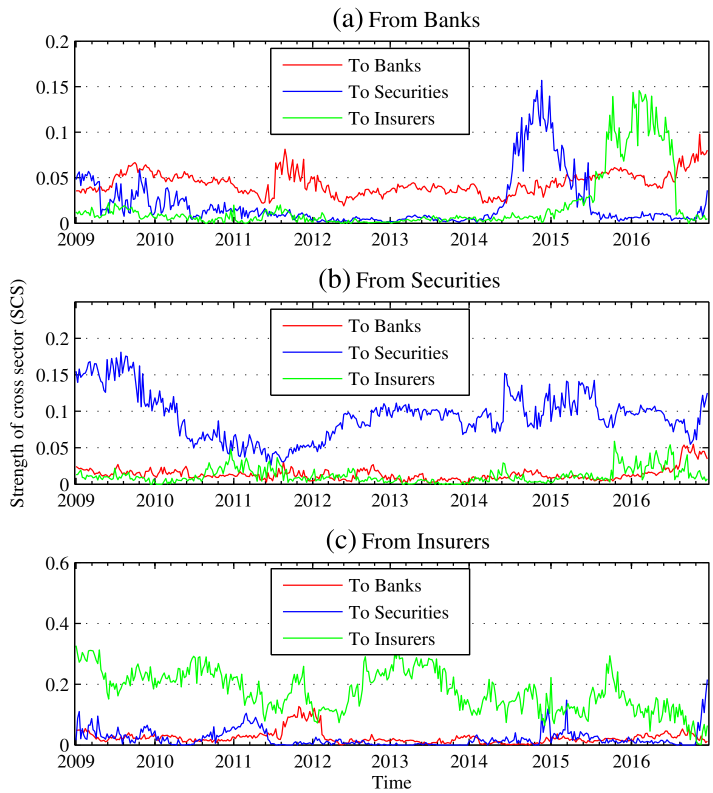

Fig. 3. Strength of cross sector (SCS) in dynamic TENETs at the 1% risk level for 24 Chinese financial institutions. SCS measures the level of the tail interconnectedness from one sector to another or itself.

G-SIBs, we examine the SRR and SRE indices of other institutions in terms of the circles and trends of the TC. In the first circle, SPDB and China Merchants Bank (CMB) had large SRR values and were thus systemically important. In the second circle only CIB consistently displayed larger SRR values and was thus the largest systemic risk contributor during that period. CIB being a potential SIFI is mainly attribute to its high level of incoming connectedness in the second circle (see Fig. 4). One of the major reasons for CIB being a potential SIFI is its interbank business. CIB is known as "interbank king" in China's financial system. It has started the bank-bank cooperation business since 2007 and owns the bank-bank cooperation service brand "Yinyin platform" which provides payment and settlement business for small and medium-sized banks. The interbank business is favored by small

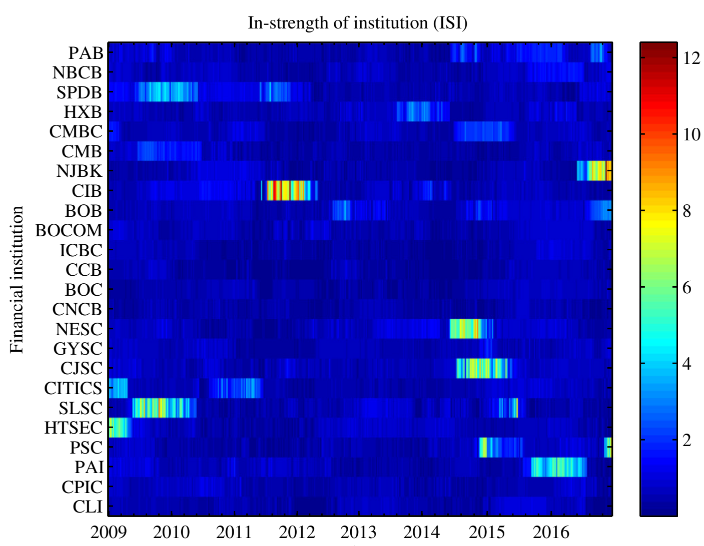

Fig. 4. In-strength of (each) institution (ISI) in dynamic TENETs at the 1% risk level for 24 Chinese financial institutions. ISI measures the level of the incoming connectedness of an institution. Notes for this and following figures: The full name of each financial institution is shown in Table 1.

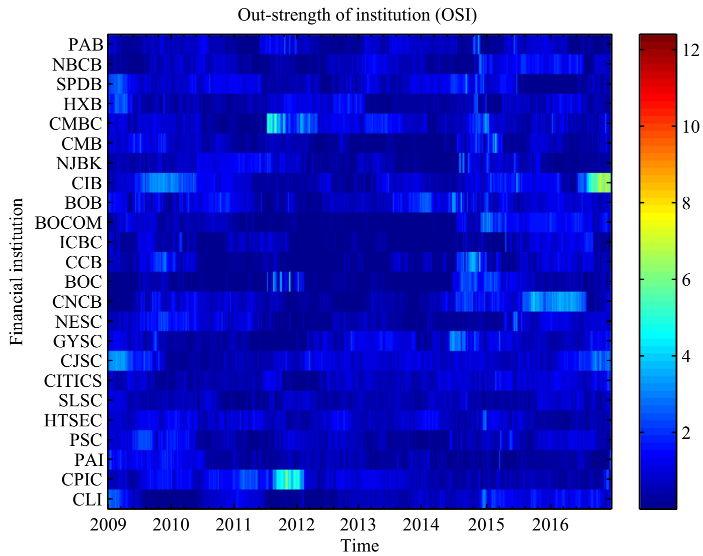

Fig. 5. Out-strength of (each) institution (OSI) in dynamic TENETs at the 1% risk level for 24 Chinese financial institutions. OSI measures the level of the outgoing connectedness of an institution.

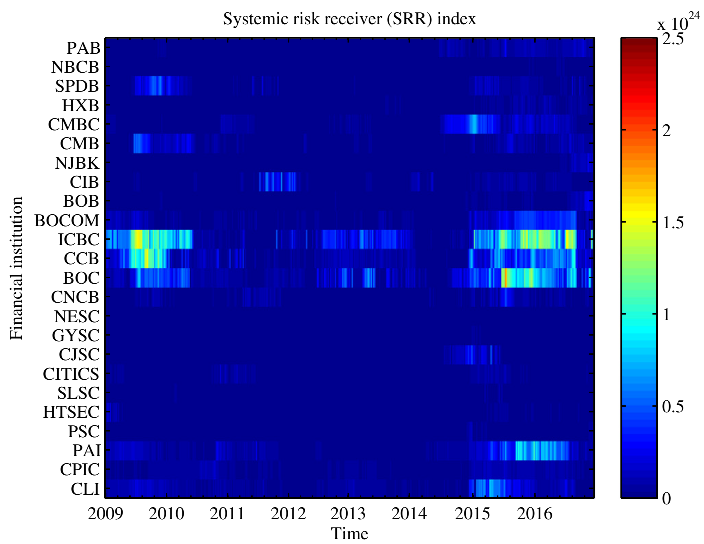

Fig. 6. Systemic risk receiver (SRR) index of each institution in dynamic TENETs at the 1% risk level for 24 Chinese financial institutions.

and medium-sized banks in China because they prefer to rely on interbank activities and wealth management products (WMPs) to increase their assets and profits. At the end of 2016, CIB's interbank liabilities reached over 1.72 trillion Yuan which accounted for one-third of its total liabilities. Credit expansion based on interbank business would contribute to the risk of China's shadow banking system. Thus, the regulatory authorities should pay more attention to CIB with large exposure to shadow banking.[22]

During the stable period, only the three G-SIBs had large SRR values. In the first phase of the third circle, six institutions, including three banks (CMBC, BOCOM, and CNBC), one securities firm (CJSC), and two insurance companies (CLI and PLA) had larger SRR values for institutions other than the three G-SIBs. Note that in this phase the connectedness of the system reached a peak (see Fig. 1), suggesting that strong tail interconnectedness in the system increases the number of systemically important financial institutions. In the second phase of the third circle, many institutions (especially banks) had large SRR values, and two institutions — the insurer PAI and the bank BOCOM — had higher SRR values than the others, except for the three G-SIBs. Our findings are significant because (i) PAI is one of the nine G-SIIs published by FSB since 2014, and (ii) BOCOM is one of the five largest commercial banks, and Zhou (2011) point out that the size of the five largest commercial banks indicate that they are systemically important. Fig. 7 shows that the evolution of each institution's SRE index indicates (i) that almost all banks except for NBCB, BOB, and NJBK and the three insurers contributed systemic risk, and (ii) that the SRE values of almost all securities

[22] Note that due to the irregularities in its interbank business, CIB was fined 3.5 million Yuan by CBRC in November 2016.

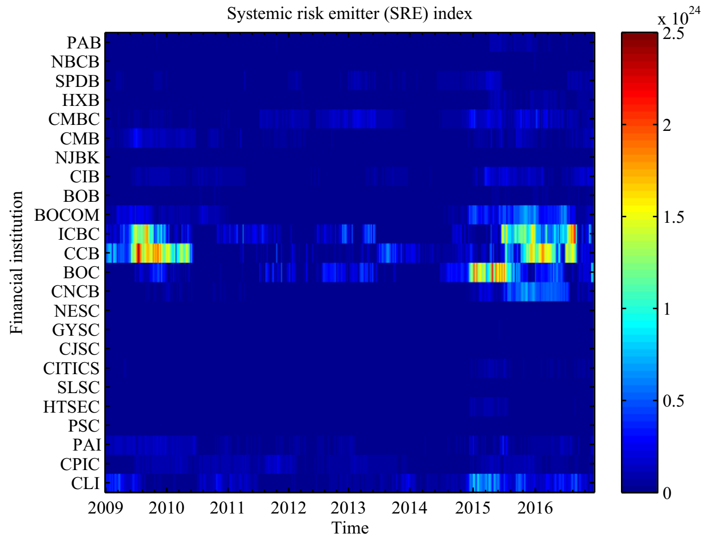

Fig. 7. Systemic risk emitter (SRE) index of each institution in dynamic TENETs at the 1% risk level for 24 Chinese financial institutions.

companies (except for CITICS and HTSEC in the third circle) are significantly smaller than those of banks and insurers, implying that their systemic risk contribution is small. Note that, in addition to the three G-SIBs, some institutions have large SRE values, e.g., (i) three banks, including CMB, CIB, and BOCOM, and the three insurers in the first circle and the following period with a decreasing trend of the TC, (ii) the bank CMBC in the second circle and the stable period, and (iii) the rest of the banks except for NBCB, BOB, and NJBK and two insurers including PAI and CLI in the third circle. Our analysis of the SRR and SRE indices suggests that regulators should pay attention to both the G-SIBs and G-SII (i.e., ICBC, BOC, CCB, and PAI) and the financial institutions with a high level of incoming and outgoing tail connectedness. Thus our findings based on TENET provide helpful information for financial regulators when establishing the list of domestic systemically-important financial institutions (D-SIFIs). Taking the banking sector as an example, except that ICBC, BOC, and CCB are recognized as G-SIBs,[23] we suggest BOCOM, CMB, CIB, CMBC, and SPDB to be included in the domestic SIBs (D-SIBs) list[24] because they have large SRR or SRE values over a long period of time. According to the regulatory requirements on commercial banks' capital management issued by CBRC, the "Big Five" large commercial banks (i.e., ICBC, CCB, BOC, ABC, and BOCOM) and CMB have been required to implement the advanced approach of capital management to calculate risk-weighted assets and capital adequacy ratio (CAR) since April 2014, and the other commercial banks still use the standard method of capital management that was implemented in January 2013. Thus CIB, CMBC, and SPDB should be required to use the advanced method to calculate risk-weighted assets and CAR when they are included in the D-SIBs list. Another important suggestion is that the regulatory authorities should formulate different regulatory standards to G-SIBs and D-SIBs rather than adopt the same standard. That is to say, the regulators should treat G-SIBs and D-SIBs differently. For example, the additional capital surcharge of D-SIBs should be lower than that of G-SIBs.

One of the major reasons of why banks contribute more to systemic risk is China's bank-dominated financial system. The indirect financing from commercial banks dominates the social financing in China, even now that financing channels have been diversified. According to the statistics of the aggregate financing to the real economy from the People's Bank of China (PBC, the central bank), the monthly-average direct financing share of the total social financing in 2016 is only 28%. After the 2008 global financial crisis, the Chinese government announced a two-year 4 trillion Yuan stimulus package to boost the domestic economy because the export demand shrank dramatically in the global recession. Commercial banks were the main channels for the 4 trillion Yuan investment,[25] and their credit ceilings were abolished to provide more credit to priority projects, the "three rural issues: agriculture, rural areas and farmers," middle and small-sized enterprises, technical innovation and industrial rationalization through mergers and acquisitions. This concentrated and massive lending inevitably led to a sharp expansion in credit and a sharp rise in the non-performing loans (NPLs),[26] resulting in that the banking sector's systemic risk contribution is higher than other financial sectors. Another possible reason is the increasing interaction between the banking sector and other financial sectors. In recent years, especially after the 4 trillion Yuan stimulus package, with the development of bank-trust, bank-securities, bank-futures, and bank-insurance cooperation businesses, credit funds through the shadow banking system flow to real estate and other high-risk markets, leading to a significant increase in the banking sector's systemic risk contribution.

[23] It should consist of ABC which is not included in our sample.

[24] Here, we consider that D-SIBs are less systemically important than G-SIBs.

[25] For example, Liu Mingkang, the (former) chairman of CBRC, at the CEO China Presidents Seminar 2011, said that the local government debt totaled 10.7 trillion Yuan in 2010 and 80% of the local government debt was bank lending.

[26] According to annual reports of CBRC, for example, as of end-2014 and end-2015, the outstanding balance of NPLs in commercial banks reached 842.6 billion Yuan and 1.27 trillion Yuan, and rose by 250.6 billion Yuan and 431.9 billion Yuan from the corresponding year earlier, i.e., grew by 42.3% and 51.3%, respectively.

We also find that the systemic importance of two insurers PAI and CLI in recent years is becoming increasingly notable. Their SRR or SRE values were larger than those of BOCOM and ranked only second to the three G-SIBs (i.e., ICBC, CCB, and BOC) during the period from end-2014 to mid-2016. This finding is closely related to the reform of the deregulation of the Chinese insurance sector. On 13 August 2014, for example, China's State Council released the *Several Opinions on Accelerating the Development of the Modern Insurance Service Industry*, aiming to by 2020 basically complete the development of a modern insurance service industry with insurance penetration (premium/GDP) of 5% and insurance density (premium/population) of 3500 Yuan per person.[27] As a result, during the 2011–2016 period, the total assets of the insurance sector rose by 152% from 6.01 trillion Yuan to 15.12 trillion Yuan. With the relaxation of regulations, more and more insurance companies get involved in high-risk businesses and are connected with more financial institutions, gradually increasing systemic importance of the insurance industry. The market seems to have captured the changes in the insurers and reflected this behavior in the price changes of their stocks.

From the above study, we see that the level of the tail interconnectedness and systemic risk reached a peak in the third circle that includes the bullish period and the period of stock market turbulence. Here, we perform a case study by examining the TENET for the 24 Chinese financial institutions on 31 December 2014, the date when the TC reached the highest level in the third circle. The network shown in Fig. 8 is the TENET at the 1% risk level for these 24 institutions on that date. Table 2 shows the top 10 edges (directional connectedness) from institution i to institution j ranked by their values of $|\hat{D}^{w}_{j|i}|$. The strongest connection is between CCB and CJSC, which accounts for 15% of the total connectedness. In the top 10 edges, we find (i) that eight start nodes are banks including three large commercial banks, and that the other two start nodes are the securities company HTSEC and the insurer CLI, and (ii) that all ten end nodes are securities companies. These findings suggest that most of the strong tail risk spillovers are from banks to securities. One potential reason for the strong tail risk spilling from banks to securities is the so-called channel business between banks and securities. The channel business means that securities engage in the profitable business of helping banks transfer their loans and notes on the books into off-balance-sheet financial products, and its resulting murky WMPs of banks and asset management products (AMPs) of securities are the cornerstone of China's shadow banking system and they could be a hidden systemic risk. According to annual operating statistics of securities released by the Securities Association of China (SAC), the size of securities' AMPs through the channel business increased rapidly from 0.28 trillion Yuan in 2011 to 17.82 trillion Yuan in 2016. A major reason for the increase of channel business is that the bank-trust cooperation products were halted by CBRC in August 2010 and were quickly replaced by the channel business. Note that CSRC fully banned the channel business between banks and securities on 19 May 2017.

To investigate the incoming and outgoing connectedness of individual institutions, Table 3 shows the top 10 financial institutions ranked by in-strength of institution (ISI) and out-strength of institution (OSI). Among the top 10 institutions ranked by ISI, there are six securities companies, three banks (CMBC, BOB and HXB), and one insurer (CLI), and most these institutions (except for CLI) have a small or moderate market capitalization. The top 10 financial institutions ranked by OSI are composed of seven banks, two securities firms (HTSEC and CITICS), and CLI. Half of them have a large market capitalization and half of them have a moderate or small market capitalization. Note that moderate or small firms also have strong incoming and outgoing connectedness when the system is distressed. To identify systemic risk contribution of financial institutions, in Table 4 we list the top 10 financial institutions ranked by the SRR and SRE indices that consider each institution's incoming and outgoing connectedness and its market capitalization. At first glance, the three G-SIBs, i.e, ICBC, CCB, and BOC, and the G-SII PAI are all in the top 10 of both the SRRs and SREs lists. In the top 10 SRRs, we find (i) that half of the SRRs are banks and all three insurers are SRRs, (ii) that the top five largest companies ranked by market capitalization are included in the SRR list, suggesting that large firms tend to have systemic importance, and (iii) two small securities companies (CJSC and PSC) are in the SRR list, indicating that small financial institutions can also contribute to systemic risk due to their high level of tail interconnectedness. The top 10 SREs include seven banks, two insurers (CLI and PAI), and one securities company (HTSEC). These 10 financial institutions have a market capitalization that is either large or moderate, suggesting that both large and moderate firms trend to being the systemic risk emitters — but note that HTSEC being a systemic risk emitter is ascribed to its strong outgoing connectedness because it has the second largest OSI (see Table 3).

5. Discussion

It is noteworthy that the validation of some empirical results in our study is based on the global SIFIs (G-SIFIs) list of FSB. The FSB uses a relatively simple indicator-based approach for identifying the G-SIFIs and regulators in many countries use the indicator-based approach of FSB as a benchmark for detecting the D-SIFIs, thus there is a big question why regulatory authorities should use a very complex method that is hard to understand. In other words, what are their motivations to use a complex method?

Although the indicator-based approaches are simple and clear, with good flexibility and operability, they have the following obvious limitations. First, they are unable to capture the contagion or spillover effect, the negative externality, and the interconnectedness of systemic risk. Second, the indicator selection and weighting in the indicator-based approaches are heavily dependent on regulators' subjectivity and experience. For example, the five categories of indicators used in the FSB assessment

[27] At that time, the rates for insurance penetration and density were about 3% and 1200 Yuan per person, respectively.

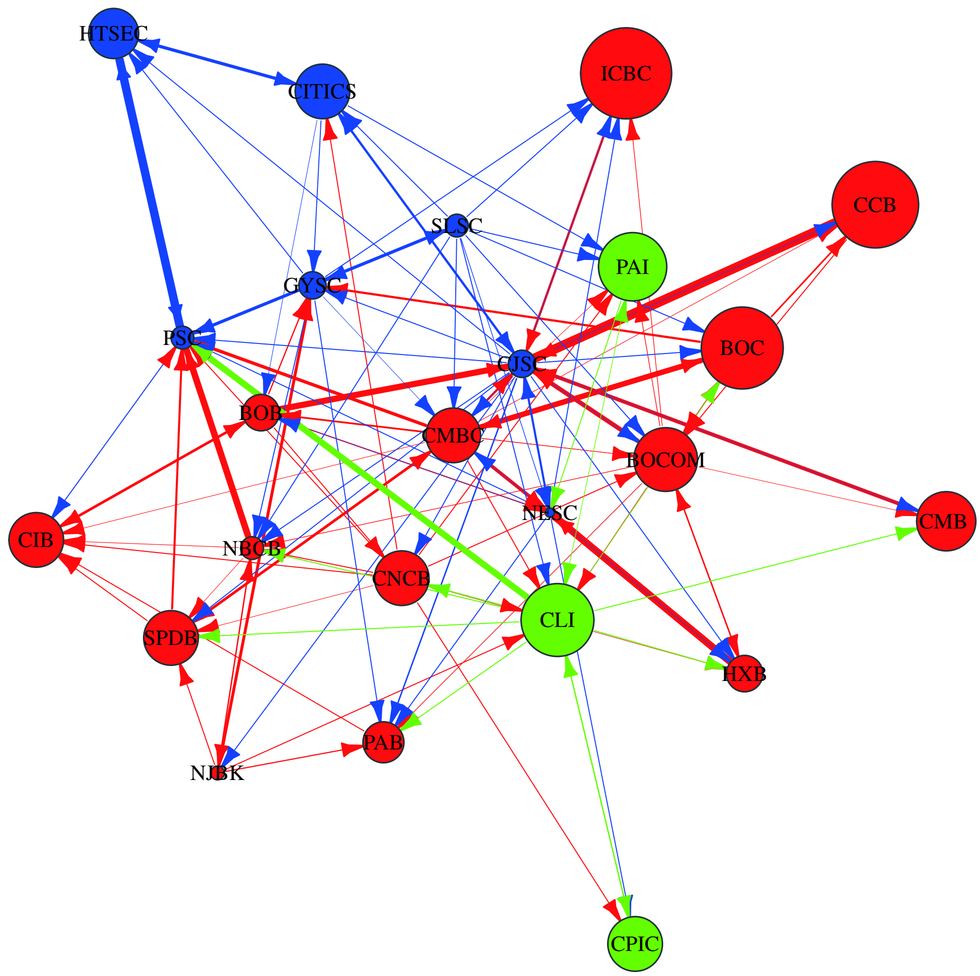

Fig. 8. Snapshot of the tail-event driven network (TENET) at the 1% risk level for 24 Chinese financial institutions on 31 December 2014. Notes: Financial institutions (nodes) from the same sector and their outgoing edges are marked by the same color. Banks, securities, and insurers are marked by red, blue, and green, respectively. The radius of each node is proportional to the market capitalization of its corresponding financial institution as of 31 December 2014. The thickness of an edge shows the relative strength of tail interconnectedness from one institution to another in the network. The thicker the edge from one node to another is, the stronger the tail interconnectedness (or the tail risk spillover) from one institution to another is.

approach are equally weighted by 20%. Third, the data of indicators are based on the accounting data such as those from the firm's annual balance sheet, thus the indicator-based approaches are backward-looking and they cannot detect the dynamics of the interconnectedness and systemic risk of financial institutions. On the contrary, the market-based methods such as the TENET using market data have the following advantages: (i) they are more forward-looking because the equity price changes (returns) of a financial institution reflect the market expectation on the firm's future performance, (ii) they are more timely,

Table 2
Top 10 edges (directional connectedness) from institution i to institution j ranked by their values of $|\hat{D}^w_{j|i}|$ in the TENET at the 1% risk level on 31 December 2014. Notes: $|\hat{D}^w_{j|i}|$ is the strength of tail interconnectedness (or tail risk spillover) from institution i to institution j. Each financial institution's full name is shown in Table 1.

Rank	From i	To j	$\lvert\hat{D}^w_{j\|i}\rvert$
1	CCB	CJSC	2.18
2	HTSEC	PSC	1.95
3	HXB	NESC	1.68
4	NBCB	PSC	1.51
5	CLI	PSC	1.46
6	BOB	CJSC	1.41
7	BOC	CMBC	1.26
8	BOCOM	CJSC	1.03
9	CMB	CJSC	0.88
10	CMBC	NESC	0.81

Table 3
Top 10 financial institutions ranked by in-strength of institution (ISI) (left panel) and out-strength of institution (OSI) (right panel) in the TENET at the 1% risk level on 31 December 2014. Notes: This table also shows the top 10 financial institutions' market capitalization (MC) and the corresponding MC rank on December 31, 2014. The value shown in the brackets is the financial institution's MC.

Rank	Name	ISI	Rank of MC	Name	OSI	Rank of MC
1	CJSC	7.25	18 (7.98E+10)	CMBC	3.57	10 (3.70E+11)
2	PSC	6.55	22 (5.02E+10)	HTSEC	2.69	14 (2.31E+11)
3	NESC	3.63	24 (3.91E+10)	BOCOM	2.40	6 (5.05E+11)
4	CMBC	2.14	10 (3.70E+11)	CLI	2.35	4 (9.65E+11)
5	GYSC	1.75	19 (6.12E+10)	BOC	2.34	3 (1.16E+12)
6	BOB	1.27	17 (1.15E+11)	CCB	2.21	2 (1.68E+12)
7	CITICS	0.78	9 (3.73E+11)	NBCB	2.04	21 (5.11E+10)
8	SLSC	0.74	20 (5.61E+10)	BOB	2.02	17 (1.15E+11)
9	CLI	0.60	4 (9.65E+11)	HXB	1.92	16 (1.20E+11)
10	HXB	0.60	16 (1.20E+11)	CITICS	1.25	9 (3.73E+11)

Table 4
Top 10 financial institutions ranked by the systemic risk receiver (SRR) index (left panel) and the systemic risk emitter (SRE) index (right panel) in the TENET at the 1% risk level on 31 December 2014. Notes: This table also shows the top 10 financial institutions' market capitalization (MC) and the corresponding MC rank on December 31, 2014. The value shown in the brackets is the financial institution's MC.

Rank	Name	SRR	Rank of MC	Name	SRE	Rank of MC
1	CCB	8.17E+23	2 (1.68E+12)	BOC	1.50E+24	3 (1.16E+12)
2	CMBC	6.12E+23	10 (3.70E+11)	CLI	4.99E+23	4 (9.65E+11)
3	CJSC	4.82E+23	18 (7.98E+10)	BOCOM	4.20E+23	6 (5.05E+11)
4	BOC	3.86E+23	3 (1.16E+12)	CMBC	3.35E+23	10 (3.70E+11)
5	CLI	3.65E+23	4 (9.65E+11)	CCB	3.15E+23	2 (1.68E+12)
6	ICBC	1.56E+23	1 (1.71E+12)	HTSEC	8.65E+22	14 (2.31E+11)
7	PAI	1.32E+23	5 (6.36E+11)	SPDB	8.00E+22	12 (2.93E+11)
8	PSC	1.21E+23	22 (5.02E+10)	PAI	7.80E+22	5 (6.36E+11)
9	CPIC	8.87E+22	13 (2.93E+11)	ICBC	7.43E+22	1 (1.71E+12)
10	CNCB	8.54E+22	8 (3.81E+11)	CNCB	7.42E+22	8 (3.81E+11)

because they can show the time-varying features of systemic risk in the financial system and can detect the potential systemic events and the major risk contribution of SIFIs, and (iii) publicly-traded market data are more easy to obtain, because most of the indicator-based data are proprietary data of financial institutions and they can be obtained only by regulators. Thus, the systemic risk measures based on market data such as equity returns of financial institutions have been widely favored by academia and regulatory authorities in the post-crisis era (see, e.g., IMF, 2009; Billio et al., 2012; Diebold and Yılmaz, 2014; Adrian and Brunnermeier, 2016; Härdle et al., 2016; Acharya et al., 2017; Brownlees and Engle, 2017).

Measuring systemic risk of financial institutions and identifying the SIFIs always require creative thinking and innovation. First, financial innovation and regulation are always dependent on each other. Early-warning indicators used in the regulatory evaluation method may fail if individual financial institutions change their behavior (e.g., developing new financial products or tools) in response to the strict regulation. Unsuitable assessment approaches would lead to overregulation on the SIFIs and this would further drive the next round of financial innovation, causing a new round of the "cat-and-mouse" game between financial institutions and regulators. Second, one of the lessons learned from the recent global financial crisis is that the regulatory pattern should not only include the microprudential regulation focusing on the risk of individual financial institutions but also include the macroprudential regulation focusing on systemic risk, which also tells us (i) that we are unable to use our existing systemic risk approaches to predict the next financial crisis and (ii) that there is no one-size-fits-all solution for measuring systemic risk. This is because systemic risk is dynamic, and any changes in the initial factors in the financial network would lead to a "butterfly effect" in the financial system. Thus developing new approaches, which should take into account dynamic changes of the complex interbehavior across financial institutions, are necessary and urgent for the SIFIs identification. In their work entitled "Complexity theory and financial regulation," Battiston et al. (2016) propose that "*economic policy needs interdisciplinary network analysis and behavioral modeling.*" Our empirical investigation on the interconnectedness and systemic risk of China's financial institutions using dynamic TENETs is a response to their proposal and provides the potential cross-check of measuring systemic risk and identifying the SIFIs based on market data.

Note that although the indicator-based approach of FSB is not good enough in measuring the interconnectedness and systemic risk of financial institutions from several aspects, we still use it as a benchmark for comparing the similarities between FSB results and our results.[28] We also show other information that cannot be detected by the FSB assessment approach. In contrast to the FSB assessment approach that only offers several global systemically important financial institutions each year, our work

[28] Having a better benchmark, there are two potential options: (i) real life experience — if something potentially good proof happened during the crisis or market crash, and (ii) simulation of contagion using interbank exposures (see, e.g., the algorithm of Eisenberg and Noe, 2001). We thank a reviewer for providing this valuable suggestion and an interesting avenue that deserves further research.

provides a full and time-varying picture of the interconnectedness and systemic risk of all financial institutions in the sample. For example, our study suggests that the D-SIBs list should include BOCOM, CMB, CIB, CMBC, and SPDB and finds that some small financial institutions are systemic risk emitters or receivers because they have a high level of outgoing or incoming connectedness. In summary, our work supplies the following additional information for regulators or corporate risk managers compared to other type of approaches (e.g., the simple indicator-based approach of FSB). First, our used approach, the TENET, can capture the contagion or spillover effect across financial institutions. The connection from one institution to another in the TENET represents their possible contagion or spillover effect. The contagion or spillover channels may largely stem from direct credit or liquidity exposure, and partly arise from serval different common factors, e.g., sector risk and exposure on common customers due to the same business model that provides homogeneous products and services. The indictors for the interconnectedness in the FSB assessment method are accounting values of intra-financial system assets, intra-financial system liabilities, and securities outstanding, which however, cannot directly reflect the contagion or spillover effect across financial institutions. Second, based on market data including equity prices, firm characteristics, and macroeconomic state variables, our study provides dynamic and forward-looking empirical results, including time-varying total connectedness, time-varying incoming and outgoing connectedness of sectors and institutions, and time-varying systemic risk receiver and emitter indices. The dynamic indicators supply an early-warning function regarding the interconnectedness and systemic risk of financial institutions to regulatory authorities and corporate risk managers. For example, the indicators including the total connectedness, the incoming and outgoing connectedness, and SRR and SRE indices reached a record high during the recent years, meaning a high level of systemic risk in the Chinese financial system. This is why a strong supervisory storm sweeps the Chinese financial sectors since the beginning of 2017. With the goals of reducing systemic risk, deleveraging, and strengthening governance of China's financial sectors, so far, new and tightened regulations include AMP leverage restrictions, the punishment of bad bank practices (e.g., related-party transactions), huge fines for stock market manipulation, and restrictions on the use of WMP funds. Third, our empirical analysis shows that an important factor for the increasing interconnectedness and systemic risk in China's financial system in recent years is the rapid expansion in shadow businesses of financial institutions. According to Moody's report, China's shadow banking assets stood at 54 trillion Yuan as of end-2015, equivalent to 78% of its GDP, and was the third largest in the world. Thus regulatory authorities should pay special attention to the increasing size of the shadow banking system that contributes to systemic risk and endangers financial stability, and this needs the interagency cooperation and information sharing between PBC, CBRC, CSRC, and CIRC.[29]

6. Conclusions

We have investigated the interconnectedness and systemic risk of 24 Chinese financial institutions using a tail-event driven network (TENET). We have built dynamic TENETs and analyzed network topological features from a system-wide, sector-conditional, and firm-level perspective. We find that the TENET has a high level of total connectedness when the system is experiencing uncertain economic conditions or is under distress. Specifically, total network connectedness reaches a peak in three circles, (i) the later period of the 2008–2009 global financial crisis, (ii) the most intense period of the European sovereign debt crisis, and (iii) the Chinese bull market period and the subsequent "2015–2016 Chinese stock market turbulence." The directional connectedness of sectors shows (i) that banks always emit the largest tail risk, followed by securities and insurers, and (ii) that most of the sector tail risk spills over into itself. The incoming and outgoing connectedness of institutions varies across time and reaches a high level when the system is under distress. We identify three Chinese G-SIBs (ICBC, BOC, and CCB) and one Chinese G-SII (PAI) released by FSB to be SRRs and SREs. Large banks and insurers usually have systemic importance. Small firms with a high level of outgoing or incoming connectedness are detected as systemic risk emitters or receivers.

Our empirical study using TENET analysis contributes to the literature on measuring systemic risk and provides useful information to regulators when measuring the systemic risk of financial institutions and determining which financial institutions are systemically important. Our work has several possible extensions for further study. First, our study focusing on the interconnectedness and systemic risk based on market data assumes that the investigated market is efficient and the equity prices of a financial institution instantly and fully reflect all relevant information and also represent the market expectation on its future business and performance. Although some special features on shares (e.g., a large proportion of state-owned shares in some listed companies) in the Chinese stock market may influence the market efficient, many studies (see, e.g., Lim et al., 2009; Wang et al., 2010; Chong et al., 2012) show that the Chinese stock market has become increasingly efficient since the non-tradable share reform in 2005. We leave the topic about the influence of the different ownership structures of financial institutions and the different size of the publicly-traded share of stocks on the market efficient for the future study. Second, the data used in our study do not include all publicly listed financial institutions in China because we have eliminated those for which we have only limited data and those that have experienced long suspension periods. Thus developing new analytical tools that can examine financial institutions for which there is limited data is a worthy goal. Another important extension would be to forecast the systemic impact and the risk of financial institutions in the TENET. This effort could use the approach described by Hautsch et al. (2014) that predicts the systemic influence of interconnected financial institutions in the system based on their proposed tail

[29] Note that in the 5th National Financial Work Conference held by the Chinese government on 14–15 July 2017, the authority announced that a new regulatory institution, the Financial Stability and Development Committee (FSDC) under the State Council, will be set up for enhancing coordination and interaction among financial regulatory organizations (i.e., PBC, CBRC, CSRC, and CIRC) and promoting information sharing.

risk interdependence network (Hautsch et al., 2015). The tail risk interdependence network of Hautsch et al. (2015) uses the linear least-absolute shrinkage and selection operator (LASSO) method to select variables and estimate the VaR of the system. TENET differs from this approach in that it uses a non-linear model (i.e., single-index quantile regression). Thus the forecast approach proposed in Hautsch et al. (2014) could be extended using the TENET model.

Acknowledgments

We are grateful to Prof. Jonathan A. Batten (the Editor-in-Chief), Prof. Péter Csóka (the subject editor), and two anonymous referees for their insightful comments and helpful suggestions. The work of GJW and CX was supported by NSFC (Grant nos. 71501066, 71373072, and 71521061), the Hunan Provincial Natural Science Foundation of China (Grant no. 2017JJ3024), and the China Scholarship Council (Grant no. 201506135022). The work of ZQJ was supported by the Shanghai Philosophy and Social Science Fund Project (Grant no. 2017BJB006) and the Fundamental Research Funds for the Central Universities (Grant no. 222201718006). The work of HES was supported by NSF Grants PHY-1505000, CMMI-1125290, and CHE-1213217, and by DTRA Grant HDTRA1-14-1-0017 and DOE Contract DE-AC07-05Id14517.

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