Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

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

China's financial network with international spillovers: A first look

Jian Yang[a,*], Ziliang Yu[b], Jun Ma[c]

[a] Center for China Financial Research, Business School, University of Colorado Denver, United States of America
[b] School of Finance, Nankai University, China
[c] Center for Finance and Development, Tsinghua University, China

A R T I C L E I N F O

Keywords:
China's financial system
Shadow bankMeoiXQv5,GU.f(xj,XzQsyst < 5f55.c

Zhou (2013), we define the systemically important financial institutions (SIFIs) as those having relatively more influence, and thus, positive net influence (influence on others minus influence from others) on other institutions in the financial network. The influence of an FI on other FIs and its net influence in the financial shock transmission network arguably reflect the comparative importance of an FI within the network.

As reviewed below, our study generally falls into the large emerging body of literature on identifying SIFIs using public market data. In this study, we use the stock returns,[2] based on a modified approach to the recently developed financial network analysis, to investigate China's financial shocks transmission network and the SIFIs in China, rather than other popular systemic risk measures used in previous studies.[3] This is so because all the current major measures on systemic risk mirror ranking of firms based on market risk or liabilities, which are (largely) reflected in the stock prices (Benoit et al., 2013, 2017).

Our study is particularly similar to Yang and Zhou (2013) and Diebold and Yilmaz, 2014. Yang and Zhou (2013) use credit default swap data to identify the structure of credit risk network across the major US and EU FIs. Diebold and Yilmaz, 2014 use stock returns to investigate the network connectedness among major US FIs based on the proposed network analysis derived from the vector autogresression (VAR) forecast error variance decomposition. Our study can be regarded as using an analytical approach combining the approaches used in these two studies, with special focus on Chinese listed FIs. First, we use the stock returns to investigate the financial transmission network among Chinese listed FIs, based on the modified Diebold and Yilmaz, 2014 network analysis. Following the two-step analytical approach proposed in Yang and Zhou (2013), we then further investigate the relevant determinants of such a network.

The study contributes in two ways. First, we contribute to a further understanding of China's financial system. Currently, the literature argues that China's financial system is still dominated by banks, especially by the Big Four (Allen et al., 2005; Berger et al., 2009; Ayyagari et al., 2010; Allen et al., 2012). As against this, we document a new finding that although banks still dominate China's financial system in terms of transmitting financial shocks, nonbank FIs' shocks already bear considerable influence on banks. This finding provides additional evidence on the importance of China's shadow banking problems during recent years (e.g., Allen et al., 2012; Tobin and Volz, 2018; Yang et al., 2019). Consistent with the importance of nonbank FIs and shadow banking problems, we also document the first empirical evidence that insurance companies in China largely resemble commercial banks on the basis of their stock market performance during the sample period.

The rest of this study is organized as follows. Section 2 reviews the literature. Section 3 describes the data. Section 4 discusses the empirical methodology. Section 5 presents the empirical results. Section 6 further explores various determinants. Section 7 concludes the study.

2. Literature review

This section provides a brief literature review to shed some light on why FIs in China may play an important role in the transmission of financial shocks.

According to the classification of Benoit et al. (2013, 2017), there is a large emerging body of literature on measuring systemic risk and identifying SIFIs using public market data, although there is an alternative approach to identify SIFIs by relying on information on positions and risk exposures. The high-frequency public market data, such as stock returns, option prices, or credit default swap spreads should reflect all information about publicly traded firms, including publicly traded FIs. Thus, using public market data should be an efficient approach to investigate the up-to-date risk transmission network as well as identify SIFIs (Huang et al., 2009; Benoit et al., 2013, 2017; Yang and Zhou, 2013; Diebold and Yilmaz, 2014).

In this regard, one might be concerned about the informational quality of stock prices on the Chinese stock market due to its unique features, although it has consistently ranked as the second-largest stock market since 2014. Hence, it is important to note that although Chinese stock prices are more volatile, Carpenter et al. (2015), among others, recently found that "since the reforms of the last decade, China's stock market has become as informative about future corporate profits as the US. Moreover, though it is a segmented market, Chinese investors price risk and other stock characteristics remarkably like investors in other large economies." Furthermore, these listed FIs are generally among the largest and the most actively traded on the Chinese stock market, further strengthening the evidence on informational quality.

From another perspective, there are also various empirical approaches to measure systemic risk that carry direct implications for risk transmission. These approaches include financial index methods (e.g., IMF, BIS, and FSB, 2009; Allahrakha et al., 2015; Glasserman and Loudis, 2015), structural methods based on asset-liability and interbank market data (e.g., Mistrulli, 2011), and the reduced-form approach based on financial market data (e.g., Adrian and Brunnermeier, 2016; Acharya et al., 2012, 2017). The empirical approach adopted in this study is a reduced-form approach similar to Diebold and Yilmaz, 2014 and Yang and Zhou (2013), which can better model the interconnectedness of FIs or risk transmission beyond the tangible business connections. While not without its own limitations, such a capacity to comprehensively capture systemic risk should be valuable, because systemic risk does come from various sources beyond tangible business connections (Benoit et al., 2013, 2017).

On the theoretical dimensions, there may be various considerations or models that can motivate systemic risk and their transmission, where we use financial shocks more or less as a proxy for systemic risk. Allen et al. (2009) point out that there are at least three types of systemic risk that have direct implications for risk transmission among various FIs. Specifically, the first is a common asset shock (e.g., a fall in real estate or stock market prices), while the second may be a contagion where the failure of one FI leads to the failure of another due to investor panics or other psychological factors. The third common type of systemic risk is the failure of one FI that coincides with the failure of many others due to highly correlated portfolios among individual FIs. While Benoit et al. (2017) also discussed largely similar channels of systemic risk transmissions among FIs (e.g., systemic risk-taking through business operations, contagion), they also made another important point unique to this body of literature—that the approach which uses market data may produce systemic measures that are not directly connected to any particular theory, and that these measures could support a more efficient regulation (p. 109). Obviously, a similar point applies in the context of investigating systemic risk transmission.

Finally, similar to this study, Yang and Zhou (2013) point out that the identification of prime senders and receivers of information in the empirical framework of the financial network corresponds well to primary and secondary firms in the theoretical model of Jarrow and Yu (2001). Note also that the current application of Diebold and Yilmaz, 2014 typically does not allow for the role of exchange centers of credit risk information to be potentially systemically important, which is additionally considered in Yang and Zhou (2013).

3. Data

We use daily stock return data to investigate the financial shock transmission network among China's FIs. As noted by Huang et al. (2009) and Benoit et al. (2013), using the asset price data of FIs has three advantages: 1) ease of access; 2) price changes incorporate market anticipation, thereby foresight; 3) high frequency, reflecting up-to-date risk transmission architecture, thereby ensuring timely financial regulation and supervision.

We collect the original stock closing prices from the CSMAR database and clean the data as follows. First, we collect the daily stock closing prices of all the financial sector companies traded on China's A-share stock market. The sample period from January 1, 2008 to December 31, 2015 yields a preliminary sample of 51 FIs publicly traded in China. The sample period starts on January 1, 2008, because nearly half of the listed banks in China went public in 2007.[6] Inclusion of more banks is important, as banks are an important source of international propagation of financial shocks (Peek and Rosengren, 1997; Imai and Takarabe, 2011; Cetorelli and

[6] During 2007, the Industrial Bank went public in February, the China CITIC Bank in April, the Bank of Communications in May, the Bank of Nanjing and the Bank of Ningbo in July, and the Bank of Beijing and the China Construction Bank in September.

Table 1
The sample and summary statistics.

Financial institution	Abbr.	Stock code	Sector	2008–2015		2011–2015	
				Mean	Std.D	Mean	Std.D
Shaanxi International Trust	SIT	000563	Trust	0.0319	3.368	0.1005	3.178
Sinolink Securities	SLS	600109	Securities	0.0061	3.508	0.0688	3.231
Guo Yuan Securities	GYS	000728	Securities	−0.0095	3.315	0.0604	2.867
Haitong Securities	HTS	600837	Securities	−0.0143	3.286	0.0456	2.744
Pacific Securities	PS	601099	Securities	−0.0436	3.296	0.0233	2.886
Changjiang Securities	CJS	000783	Securities	−0.0047	3.360	0.0664	2.926
CITIC Securities	CS	600030	Securities	−0.0267	3.031	0.0393	2.704
Northeast Securities	NES	000686	Securities	−0.0051	3.491	0.0381	3.076
Ping An Insurance (Group) Company of China	PAI	601318	Insurance	−0.0134	2.606	0.0225	2.209
China Life Insurance Company Limited	CLI	601628	Insurance	−0.0330	2.587	0.0241	2.320
China Pacific Insurance (Group) Co., Ltd.	CPI	601601	Insurance	−0.0236	2.676	0.0209	2.316
Huaxia Bank	HXB	600015	Bank	0.0024	2.614	0.0437	2.164
Bank of China	BOC	601988	Bank	−0.0245	1.833	0.0196	1.695
Bank of Nanjing	BON	601009	Bank	0.0057	2.466	0.0515	2.158
China Merchants Bank	CMB	600036	Bank	−0.0293	2.386	0.0277	1.926
Industrial Bank	IB	601166	Bank	−0.0049	2.681	0.0459	2.236
Industrial and Commercial Bank of China	ICBC	601398	Bank	−0.0292	1.780	0.0078	1.509
Bank of Ningbo	BN	002142	Bank	−0.0036	2.580	0.0358	2.293
Ping An Bank	PAB	000001	Bank	−0.0104	2.682	0.0326	2.323
China Minsheng Bank	MSB	600016	Bank	−0.0027	2.370	0.0637	2.108
China Construction Bank	CCB	601939	Bank	−0.0242	1.961	0.0208	1.752
China CITIC Bank	CB	601998	Bank	−0.0156	2.497	0.0282	2.324
Bank of Beijing	BB	601169	Bank	−0.0167	2.436	0.0193	2.101
Bank of Communications	BC	601328	Bank	−0.0402	2.239	0.0185	1.938
Shanghai Pudong Development Bank	PDB	600000	Bank	−0.0142	2.589	0.0463	2.056
New financial institutions included during 2011–2015							
Huatai Securities	HuaT	601688	Securities			0.0349	2.870
Guangfa Securities	GFS	000776	Securities			−0.0228	2.901
China Merchants Securities	CMS	600999	Securities			0.0311	2.775
Industrial Securities	IS	601377	Securities			0.0213	3.055
Everbright Securities	ES	601788	Securities			0.0426	2.950
Agricultural Bank of China	AB	601288	Bank			0.0167	1.587
China Everbright Bank	EB	601818	Bank			0.0055	2.017

Notes: Abbr. represents name abbreviations for financial institutions. Std.D means standard deviation. There were 1945 and 1213 observations during 2008–2015 and 2011–2015, respectively.

Goldberg, 2012; Schnabl, 2012; Kamber and Thoenissen, 2013; Alpanda and Aysun, 2014). Moreover, China's financial system has been traditionally dominated by banks, especially by the Big Four. Hence, the beginning of the sample period enables us to include a sufficient number of listed banks (14 banks, including three of the Big Four) while also facilitating an examination of the impact of the 2008 global financial crisis. As a robustness check below, we also consider an alternative sample period starting on January 1, 2011 which incorporates all the 16 currently listed banks in China (including all the Big Four).

Second, we exclude the institutions that cannot satisfy the following two conditions from the preliminary sample: 1) the stock is continuously traded during the sample period without being suspended for a substantial time period; 2) the missing observations are on average fewer than 20 trading days (one month) per year. Then, we obtain a final sample of 25 FIs (including 14 banks) between 2008 and 2015 and 32 FIs (including 16 banks) between 2011 and 2015.

Third, a few missing observations of FIs are replaced by the non-missing values of previous trading days. The stock returns are then calculated as the logarithmic change of the closing prices. As the prices of China's A-share stocks (except the ST-stocks) have been limited to ± 10% fluctuations during each trading day since December 16, 1996, we replace the return value with 9.531 (−9.531) if it is higher (lower) than 10% (−10%). The details about FIs, their basic information, and the summary statistics for their stock returns are presented in Table 1.

Although the capital account is still under strict control, China is one of the world's largest countries in terms of international trade (ranked number one since 2013). Furthermore, the country holds the world's largest foreign exchange reserves. Trade is an important channel of international transmission of financial shocks. Hence, given strong economic linkages between China and the rest of the world, the empirical results of spillovers on FIs within China may well be biased without controlling for the influence from the global financial sector. Thus, the analysis also includes financial sectors of four major economies, that is, the US, the UK, Germany, and Japan. We obtain the daily US, UK, and German financial sector indices.[7] However, we cannot find a similar composite

[7] In the following robustness check, we also consider using bank indices instead of financial sector indices and the basic results remain the same.

financial sector index for Japan, as there are four Tokyo Stock Exchange indices that exist separately for banks, securities firms, insurance companies, and other financial firms in Japan. Accordingly, we conducted a principal component analysis to extract the common factors underlying these four indices. The first principal component explains approximately 84% of the variation in these four indices, which is high enough to capture the common movements in the financial sector (Yang and Zhou, 2013).[8] We thus use it as a proxy for the financial sector index in Japan. The original data of the UK and Japanese indices are collected from the CEIC database, while the US index data are collected from the website of S&P Dow Jones Indices (http://us.spindices.com/), and the German index data are collected from Bloomberg.

4. Empirical methodology

We propose a modification to recently developed financial network analysis (Diebold and Yilmaz, 2014) to investigate the transmission of financial shocks among Chinese FIs. The approach is built on forecast error variance decomposition of Generalized Vector Autoregression (GVAR; Pesaran and Shin, 1998; Yang et al., 2006), which provides natural and insightful measures of connectedness to explore the weighted and directed networks (Diebold and Yilmaz, 2014). As the first step, we assume the data-generating process of the stock returns of Chinese FIs and the financial sectors of the four major foreign countries (i.e., the US, the UK, Germany, and Japan) follow an N-dimensional covariance-stationary VAR system:

$$\boldsymbol{X_t} = \sum_{\boldsymbol{i}=1}^{\boldsymbol{p}} \Phi_{\boldsymbol{i}} \boldsymbol{X}_{\boldsymbol{t}-1} + \alpha + \varepsilon_{\boldsymbol{t}} \tag{1}$$

where X is a vector of the stock (or financial market) returns, α is the deterministic component of the VAR system, and $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances.

The moving average representation of Eq. (1) can then be written as $X = \sum_{i=0}^{\infty} A_{i\ \ t-i}$, where A_i is the $N \times N$ coefficient matrix obeying the recursive rule of $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, and A_0 is an $N \times N$ identity matrix with $A_0 = 0$ for $i < 0$. The estimated coefficients of (1) are difficult to interpret due to overparameterized and complicated interactions among the variables. As a consequence, the moving average coefficients (or their further transformations such as impulse-response functions or variance decompositions) are the key elements for understanding the dynamics of the system. We use the equation to conduct a forecast error variance decomposition under the GVAR framework, which allows us to assess the fraction of the H-step-ahead error variance of forecasting X_i that is due to $X_j (i \neq j)$ invariant to the order of the variables.[9]

The GVAR H-step-ahead error variance decomposition, $\widetilde{d}_{ij}^{gH}$ for H = 1, 2, $\cdots$, is

$$\widetilde{d}_{ij}^{gH} = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e' A_h \sum A_h' e_j)} \tag{2}$$

where Σ is the variance matrix, ε, σ_{jj} is the standard deviation of the error term for the j-th equation and e_i is the selection vector, with the i-th element equal to one, and all other elements equal to zero. The sum of all the elements in each row of the variance decomposition table under the GVAR framework is not equal to one. Therefore, following Yang et al. (2006) and Diebold and Yilmaz, 2014, we normalize each entry of the variance decomposition matrix by its row sum:

$$d_{ij}^{gH} = \frac{\widetilde{d}_{ij}^{gH}}{\sum_{j=1}^{N} \widetilde{d}_{ij}^{gH}} \tag{3}$$

Then, based on such GVAR forecast error variance decomposition, the population financial shock transmission network can be fully shown in the connectedness table. The connectedness table (Table 2) demonstrates the central understanding of the various connectedness measures and their relationships. Its main upper-left N × N block contains the variance decompositions, with d_{ij}^{H} denoting the ij − th H − step variance decomposition component. Hence, according to Diebold and Yilmaz, 2014, we define the *pairwise directional connectedness* from j to i as:

$$\boldsymbol{C}_{\boldsymbol{i} \leftarrow \boldsymbol{j}}^{\boldsymbol{H}} = \boldsymbol{d}_{\boldsymbol{ij}}^{\boldsymbol{H}} \tag{4}$$

Note that $C_{i \leftarrow j}{}^{H} \neq C_{j \leftarrow i}{}^{H}$, so there are $N^2 - N$ separate pairwise directional connectedness measures. Then we can define the *net pairwise directional connectedness* as:

$$C_{ij}^{H} = C_{j \leftarrow i}^{H} - C_{i \leftarrow j}^{H} \tag{5}$$

[8] The KMO values, which evaluate the soundness of the principal component analysis, are all above 0.8 for the overall principal component analysis and for each of the four indices.

[9] H is the connectedness horizon in the connectedness (will be demonstrated in detail later). Choosing such a horizon, as pointed out by Diebold and Yilmaz (2014), is important because it is related to issues of dynamic connectedness (in the fashion of spillovers) as opposed to purely contemporaneous connectedness. In this study, we choose 10 as the connectedness horizon, as it coheres with the 10-day value at risk required by the Basel Accord. Choosing other horizons around the value 10 might provide a way of “robustness checks,” but the actual values of the connectedness might not remain similar with alternative Hs. See Diebold and Yilmaz (2014) for more details.

Table 2
Connectedness table schematic.

	x_1	x_2	⋯	x_N	From others
x_1	$d_{11}{}^H$	$d_{12}{}^H$	⋯	$d_{1N}{}^H$	$\sum_{j=1}{}^N d_{1j}{}^H$, j ≠ 1
x_2	$d_{21}{}^H$	$d_{22}{}^H$	⋯	$d_{2N}{}^H$	$\sum_{j=1}{}^N d_{2j}{}^H$, j ≠ 2
⋮	⋮	⋮	⋱	⋮	⋮
x_N	$d_{N1}{}^H$	$d_{N2}{}^H$	⋯	$d_{NN}{}^H$	$\sum_{j=1}{}^N d_{Nj}{}^H$, j ≠ N
To others	$\sum_{i=1}{}^N d_{i1}{}^H$, i ≠ 1	$\sum_{i=1}{}^N d_{i2}{}^H$, i ≠ 2	⋯	$\sum_{i=1}{}^N d_{iN}{}^H$, i ≠ N	$\frac{1}{N}\sum_{i,j=1}^{N} d_{ij}^H$, i≠j

Source: Diebold and Yilmaz (2014).

The *total directional connectedness from others to i* are defined as:

$$C_{i\leftarrow \bullet}^{H} = \sum_{j=1, i\neq j}^{N} d_{ij}^{H} \tag{6}$$

The *total directional connectedness to others from i* is:

$$C_{\bullet\leftarrow i}^{H} = \sum_{i=1, i\neq j}^{N} d_{ij}^{H} \tag{7}$$

Then, the *net total directional connectedness* is:

$$C_{i}^{H} = C_{\bullet\leftarrow i}^{H} - C_{i\leftarrow \bullet}^{H} \tag{8}$$

The *total connectedness* can be calculated as:

$$C^{H} = \frac{1}{N}\sum_{i,j=1, i\neq j}^{N} d_{ij}^{H} \tag{9}$$

According to Diebold and Yilmaz, 2014, the SIFIs in the above connectedness network can be defined as the ones with relatively high *total directional connectedness to others* and thus positive *net total directional connectedness*. Then, the time-varying connectedness can be obtained using the fixed rolling window approach. We follow Yang and Zhou (2013) to conduct further analysis for the determinants of such financial shock transmission network, which will be illustrated in detail later.

Finally, some important comments are in order on the modified approach proposed in this study. First, it should be noted that controlling for the influence from the financial sectors of the four major global economies on individual FIs in China is a significant difference between our empirical framework and the financial network approach proposed by Diebold and Yilmaz, 2014. This modification can thus be expected to improve the informational efficiency and accuracy of the VAR system. Without controlling for the influence from the financial sectors of the major global economies, as pointed by Kilian and Lütkepohl (2017), such a VAR system may suffer from an omitted-variable bias and become informationally deficient.

Second, the modified approach allows for more flexibility in recovering the structure of the financial network. As the financial network is composed of individual FIs, the starting point of the financial network analysis (e.g., Diebold and Yilmaz, 2014; Yang and Zhou, 2013) naturally focuses on the spillovers among individual FIs from the perspective of connectedness. However, unlike previous studies, our modified approach enables us to reveal the structure of financial network based on subgroups of individual FIs (however defined), rather than the information on individual FIs or the aggregate information across all FIs.

5. Full sample results and robustness checks

5.1. Baseline results

In what follows, we present the full sample results on the transmission of financial shocks among 25 FIs while controlling for the influences from the financial sectors of the four major global economies (i.e., the US, the UK, Germany, and Japan). Following Diebold and Yilmaz, 2014, we identify the institutions with higher positive net total directional connectedness and higher total directional connectedness to others in the financial shock transmission network as SIFIs. We also briefly address the total directional connectedness from others when discussing the financial shock transmission network below.

We model the stock returns of the 25 FIs and the financial sectors of the four global economies[10] as a 1-lag VAR system with the optimal lag in Eq. (1) being selected by minimizing the Akaike Information Criterion.[11] Similar to previous studies, we calculate the full sample connectedness based on 10-step-ahead (i.e., two weeks) generalized forecast error variance decomposition. Table 3 shows

[10] Following Bessler and Yang (2003), the four global financial sectors are modeled on a same calendar day basis with China. We will discuss the nonsynchronous trading problem later.

[11] The maximum lag allowed is set to 15 days (3 weeks).

Table 3

Full sample connectedness of 25 financial institutions and 4 major global financial sectors, 2008–2015.

	SIT	SLS	GYS	HTS	PS	CJS	CS	NES	PAI	CLI	CPI	HXB	BOC	BON	CMB	IB	ICBC	BN	PAB	MSB	CCB	CB	BB	BC	PDB	USF	UKF	JPF	GMF	From
SIT	11	4.3	5.5	4.9	5.2	5.4	5	5.3	3.4	3.7	3.9	3.3	2.3	3.5	2.9	3.2	2.2	3.9	3.4	2.9	2.6	2.8	3.1	2.9	3	0.1	0.2	0.2	0.1	89
SLS	4.4	11.2	6.7	6	6.2	6.3	5.9	6.4	3.4	3.6	3.5	2.6	2	3	2.6	2.8	2	3.3	2.9	2.4	2.3	2.5	2.6	2.3	2.7	0.1	0.1	0.2	0.1	89
GYS	4.7	5.6	9.4	6	5.9	6.6	5.9	6.5	3.5	3.7	3.8	2.8	2.1	3.2	2.6	2.9	2.1	3.5	3	2.5	2.5	2.4	2.7	2.6	2.7	0.1	0.1	0.1	0.1	91
HTS	4	4.8	5.8	9	5.3	6.2	6.6	5.6	3.6	3.8	4	3.2	2.3	3.1	3	3.3	2.3	3.4	3.2	2.8	2.7	2.8	3.1	2.8	3	0	0.1	0.2	0.1	91
PS	4.7	5.5	6.2	5.8	9.9	6.3	5.9	6.1	3.4	3.7	3.6	3	2.2	3.2	2.8	2.9	2.2	3.4	2.9	2.5	2.7	2.6	2.7	2.6	2.8	0.1	0.1	0.2	0.1	90
CJS	4.4	5.1	6.3	6.3	5.7	9	6.3	6.4	3.3	3.7	3.6	3	2.2	3.2	2.7	3	2.2	3.5	3.1	2.7	2.6	2.6	2.9	2.8	2.9	0.1	0.1	0.2	0.1	91
CS	3.8	4.5	5.3	6.2	5	5.8	8.4	5.3	3.8	4.2	4.1	3.3	2.4	3.2	3.2	3.5	2.3	3.5	3.4	2.8	2.9	2.9	3	2.9	3.5	0.1	0.1	0.3	0.1	92
NES	4.6	5.4	6.6	5.9	5.8	6.7	6	9.5	3.4	3.6	3.7	2.9	2.3	3.1	2.7	3	2.1	3.5	3.1	2.6	2.6	2.6	2.7	2.5	2.8	0.1	0.1	0.2	0.1	91
PAI	2.7	2.6	3.2	3.4	3	3.2	3.9	3.1	8.5	5.7	5.9	4	3.2	3.6	4.3	4.1	3.1	3.7	4.1	3.7	3.8	3.3	3.8	4.1	3.8	0.4	0.5	0.5	0.4	91
CLI	2.8	2.7	3.3	3.6	3.1	3.4	4.1	3.2	5.6	8.4	6.1	3.9	3.4	3.6	4	3.9	3.4	3.8	3.7	3.9	3.9	3.6	3.6	4	3.6	0.2	0.3	0.4	0.3	92
CPI	3	2.6	3.4	3.7	3.1	3.4	4	3.2	5.8	6	8.3	4	3.2	3.7	4	4	3.2	3.9	3.8	3.8	3.7	3.4	3.9	4	3.6	0.2	0.3	0.4	0.3	92
HXB	2.3	1.8	2.3	2.8	2.3	2.5	3	2.3	3.6	3.6	3.7	7.6	3.8	4.7	5.3	5.3	3.8	4.8	4.9	5	4.3	4.4	4.9	4.8	5.2	0.1	0.2	0.3	0.2	92

the results echoing the schematic shown in Table 2. The result in Table 3 presents two novel findings concerning China's financial system: 1) the strikingly high total directional connectedness from others; 2) the high total directional connectedness to others and consequently, the high net total directional connectedness of the market-oriented commercial banks compared to the Big Four. In developed countries, business connection or borrowing–lending linkage is a major determinant of interconnectedness among FIs (e.g., Acharya et al., 2012; Acemoglu et al., 2012, 2015). Arguably, either business connection or borrowing–lending linkage strength may be enhanced in a more developed and integrated financial market. Additionally, an FI may be more influenced by other institutions with more exposure. Compared to the US financial market, the development of China's financial market lags and remains relatively underdeveloped. However, compared to the 70%–82% total directional connectedness from others of US FIs (Diebold and Yilmaz, 2014, Table 3, p. 126), the 89%–92% total directional connectedness from others of China's major FIs is noticeably higher. A plausible explanation for this phenomenon is that as China's financial system is still strongly controlled by the government, the asset prices of FIs share similar pricing factor, rather than being influenced by stronger inter-institution business connection. The pairwise inter-institution connection actually is indeed lower in China (Table 3) than the US (Diebold and Yilmaz, 2014, Table 3, p. 126). We can still obtain a higher total directional connectedness from others because we include more FIs in our sample and control for the influence from the financial sectors of the four major global economies.

Another interesting result presented in Table 3 is the more pronounced average influence of the market-oriented joint-stock commercial banks compared to the Big Four in the transmission of financial shocks. This finding extends the conventional argument regarding the role of banks as an important source of propagation of financial shocks (Peek and Rosengren, 1997; Imai and Takarabe, 2011; Cetorelli and Goldberg, 2012; Schnabl, 2012; Kamber and Thoenissen, 2013; Alpanda and Aysun, 2014). Although China's financial system is dominated by a large but under-developed banking system, especially the Big Four, the result presented here shows that market-oriented commercial banks (especially Huaxia Bank (HXB), China Merchants Bank (CMB), Industrial Bank (IB), Bank of Ningbo (BN), Ping An Bank (PAB), Bank of Communications (BC), and Shanghai Pudong Development Bank (PDB)) have much higher total directional connectedness to others on average (and thus a higher net total directional connectedness) than the Big Four in terms of financial shock transmission during the sample period. In line with Diebold and Yilmaz, 2014, such a finding would imply that these market-oriented joint-stock commercial banks might also need to receive more attention in the identification of SIFIs in China, perhaps a reflection of their more aggressive risk-taking culture. The finding is consistent with the recent evidence that the Big Four have dramatically improved their performance and have higher credit quality in their loan portfolio than market-oriented joint-stock commercial banks. This has been the case since the commencement of Chinese banking reforms in 2004, when the Big Four had major loan problems (Bailey et al., 2011; Hao et al., 2014). The result is also consistent with the finding that joint-stock banks have the highest persistence in both profit and risk (Lee and Hsieh, 2013). It further extends the evidence that joint-stock banks are the most technically efficient, while larger commercial banks, including the Big Four, are less technically efficient in generating deposits and loans (Huang et al., 2017), as such technical efficiency does not yet address the associated risk issue such as aggressive risk-taking. Anecdotal evidence and news reports indeed verify such a concern for some joint-stock banks.[12] Moreover, the three FIs in the insurance industry (i.e., PAI, CLI, and CPI) also exhibit an average influence resembling that of the market-oriented commercial banks, consistent with the well-known problem of aggressive risk-taking within the Chinese insurance industry during the sample period.

Of course, the more pronounced role of market-oriented joint-stock commercial banks and the emerging influence of nonbank FIs do not mean that Big Four are not important in terms of transmission of financial shocks. Rather, these findings reflect the new development of China's financial system. Since China's government began to solve the problem of non-performing loans (NPLs) in the state-owned banking system (especially for Big Four) during the late 1990s, China's banking system has undergone a series of market-oriented reforms. After addressing the NPL problem and subsequently receiving a substantial capital injection in the early 2000s, all the Big Four went public by 2010. In 2016, four of the top six banks in the world ranked by assets included the Big Four. Additionally, most of the market-oriented joint-stock commercial banks in the sample ranked among the top 50 in the world. Hence, the result might reflect that the Big Four were already under stricter supervision due to "too big to fail" concerns, with correspondingly limited operational risk-taking and potential spillovers of financial shocks in the financial system. As a further confirmation, according to Moody's Investors Service, during 2012–2015, risky wealth management product holdings as a fraction of total assets remained steady at approximately 2% for the Big Four, while these holdings increased between 2013 and 2015 for joint-stock commercial banks and local banks, reaching approximately 20% in 2015.

To further explore the pattern of financial shock spillover across various sub-sectors, we recalculate the connectedness among sectors as well as the financial sectors of the four major global economies. Table 4 reports the total directional connectedness to each institution (or market) from each subsector (or global financial market). For FIs in the securities sector, total directional connectedness from the trust, insurance, and banking sectors is approximately 4.4%, 11%, and 39%, respectively. For FIs in the insurance sector, the average total connectedness from the trust, securities, and banking sectors is approximately 2.8%, 23%, and 52%, respectively. For FIs in the banking sector, average total directional connectedness from the trust, securities, and insurance sectors is approximately 2.2%, 17%, and 11%, respectively, with total directional connectedness from nonbank FIs exceeding 30%. Therefore, although China's financial system remains dominated by the banking sector, nonbank FIs also exert considerable influence in the financial shock transmission network. China's financial system, especially the banking sector, also exerts considerable influence on

[12] Reuters. "Shanghai Pudong Development Bank's Chengdu Branch Fined By Regulator Due To Providing Loans Illegally." January 19, 2018. The fine was 462 million yuan or $72 million, and the bad loan involved was 77.5 billion yuan or $12 billion. Interestingly, Pu Dong was identified as a major sender of risk in this study before the incident was known to the public.

Table 4
Total directional connectedness from each sector/market, 2008–2015.

	Total directional connectedness from								Nonbanks	
	Trust	Securities	Insurance	Bank	USF	UKF	JPF	GMF		4GFM
SIT	11	35.6	11	42	0.1	0.2	0.2	0.1	57.6	0.6
SLS	4.4	48.7	10.5	36	0.1	0.1	0.2	0.1	63.6	0.5
GYS	4.7	45.9	11	37.6	0.1	0.1	0.1	0.1	61.6	0.4
HTS	4	43.3	11.4	41	0	0.1	0.2	0.1	58.7	0.4
PS	4.7	45.7	10.7	38.5	0.1	0.1	0.2	0.1	61.1	0.5
CJS	4.4	45.1	10.6	39.4	0.1	0.1	0.2	0.1	60.1	0.5
CS	3.8	40.5	12.1	42.8	0.1	0.1	0.3	0.1	56.4	0.6
NES	4.6	45.9	10.7	38.5	0.1	0.1	0.2	0.1	61.2	0.5
PAI	2.7	22.4	20.1	52.6	0.4	0.5	0.5	0.4	45.2	1.8
CLI	2.8	23.4	20.1	52.3	0.2	0.3	0.4	0.3	46.3	1.2
CPI	3	23.4	20.1	52.2	0.2	0.3	0.4	0.3	46.5	1.2
HXB	2.3	17	10.9	68.8	0.1	0.2	0.3	0.2	30.2	0.8
BOC	1.9	15.4	10.9	71.1	0.1	0.2	0.3	0.1	28.2	0.7
BON	2.5	18.8	10.5	67.4	0.1	0.2	0.3	0.1	31.8	0.7
CMB	2	16.3	11.4	68.8	0.2	0.3	0.4	0.3	29.7	1.2
IB	2.3	17.4	10.7	68.6	0.1	0.3	0.3	0.2	30.4	0.9
ICBC	2	15.2	10.8	70.9	0.2	0.3	0.3	0.2	28	1
BN	2.7	19.6	10.3	67	0.1	0.2	0.2	0.1	32.6	0.6
PAB	2.5	18.1	10.9	67.6	0.1	0.2	0.3	0.1	31.5	0.7
MSB	2.2	15.9	11	70.1	0.1	0.3	0.2	0.2	29.1	0.8
CCB	2	16.3	11.5	69.3	0.2	0.3	0.3	0.2	29.8	1
CB	2.2	17	10.7	69.3	0.1	0.2	0.3	0.2	29.9	0.8
BB	2.3	16.9	10.9	69.3	0.1	0.2	0.3	0.2	30.1	0.8
BC	2.1	15.6	11.4	69.4	0.3	0.4	0.4	0.3	29.1	1.4
PDB	2.2	17.8	10.5	68.6	0.1	0.3	0.3	0.2	30.5	0.9
USF	0	0.2	0.6	1.7	63.1	20.8	1	12.6	0.8	97.5
UKF	0.3	2	3.4	11.5	17.8	42.7	3.4	18.8	5.7	82.7
JPF	0.5	6.1	5.7	20.4	10.4	11	39	6.8	12.3	67.2
GMF	0.3	1.9	3.1	10	13.2	21.1	3.1	47.2	5.3	84.6

Notes: This table reports the total directional connectedness of the 25 financial institutions and 4 global financial sectors from each sector (Trust, Securities, Insurance, and Bank) or global financial market (US, UK, Japan, and Germany). USF, UKF, JPF, and GMF in the table are the abbreviations for the US financial market, UK financial market, Japanese financial market, and German financial market, respectively. Nonbanks: the nonbank financial sector. 4GFM: all four global financial sectors.

the financial sectors of the four major global economies. The total directional connectedness to the US, UK, Japanese, and German financial sectors from China's banking sector is 1.7%, 11.5%, 20.4%, and 10%, respectively, while it is 0.8%, 5.7%, 12.3%, and 5.3%, respectively, from China's nonbank FIs in aggregate. China's financial sector shows a positive net pairwise directional connectedness to three out of the four global financial sectors (i.e., UK, Japanese, and German). The total directional connectedness to China's financial sector (i.e., the 25 institutions) from the US, the UK, Japan, and Germany is 3.4%, 5.6%, 7.1%, and 4.4%, respectively, while the total directional connectedness to the US, the UK, Japan, and Germany from China is 2.5%, 17.2%, 32.7%, and 15.3%, respectively. The net pairwise directional connectedness between China and the US, the UK, Japan, and Germany is −0.9%, 11.6%, 25.6%, and 10.9%, respectively. Thus, China's financial sector exerts considerable influence on the financial sectors of the major global economies, especially the Japanese financial sector. This may be attributable to China's economic growth, strict capital controls, and its growing importance in the world economy, particularly in the regional economy.

5.2. Robustness checks

We conduct several robustness checks on the main results above. The first robustness check is to use the banking sector indices instead of financial sector indices to control for the influence from the financial sectors of the four major global economies.[13] As discussed earlier, we focus on bank-dominated China's financial system, and banks can be both an important source of international propagation of financial shocks and an important channel for transmitting them. Accordingly, it might be important to determine whether the transmission pattern of financial shocks among China's FIs will change if we restrict the outside influence only to that from the banking sector, instead of the entire financial sector.

The second robustness check investigates the potential nonsynchronous trading problem. In line with Bessler and Yang (2003), our main previous results are based on modeling all financial market data matched on the same calendar day. Trading in the European (UK and German) and North American (the US) stock markets lags behind China's and Japan's on the same calendar day.

[13] We still use the financial sector index for Germany, as we cannot find a readily available banking sector index.

Combining this fact with the GVAR forecast error variance decomposition, this implies that the stock markets of Japan and China are the leading markets. Therefore, following Bessler and Yang (2003), we model the US, UK, and German markets as the leading markets in the VAR system as our second robustness check.

The third robustness check is to incorporate more FIS in our sample. During 2008–2015, a number of FIs went public in China, including the last of the Big Four—the Agricultural Bank of China. We thus redefine the sample period starting from 2011 rather than 2008 to incorporate seven extra institutions in the sample, which results in 32 FIs during 2011–2015, including all the Big Four.

The fourth robustness check is to examine whether our basic results are mainly driven by the impact of common components or common factors to Chinese FIs, although macroeconomic factors may play a role (as shown below). One might argue that the high detected connectedness among China's FIs may well be caused by common trends of the stock market prices as a proxy for overall expectations of fundamentals, or common factors that drives the stock prices rather than truly reflect interconnectedness. To address this issue, we filter out all of)cNofstock gesura5fs ry
T t 5Ufee ≠ X@v5,G*v0U,x.,G5X‘v + Ncf.elora5(sOGf5UW(,NtleOGffU0.fU0fU)fl,X5t t 55. d ?5f.e r t 5(ion t 55.

to others, and thus lower net total directional connectedness (highly negative) for the financial sectors of the four major global economies. Hence, if we model the analysis on this alternative definition of a trading day, China's financial sector would exhibit even higher influence on global financial sectors.[14]

The result derived from the alternative sample including 32 FIs during 2011–2015 is also very close to our main previous results. Similar to the other three, the Agricultural Bank of China, the latest of the Big Four to go public, also has lower total directional connectedness to others, and thus, a lower net total directional connectedness in the financial shock transmission network. Moreover, the total directional connectedness from all other FIs is somewhat higher than during 2008–2015. The total directional connectedness to the financial sectors of the four major global economies from China also increases substantially (Appendix Tables A-2 and A-3). More interestingly, the other nonbank FIs, especially several institutions in the securities sector, emerge to manifest considerable influence in the financial shock transmission network. These results again reflect the recent

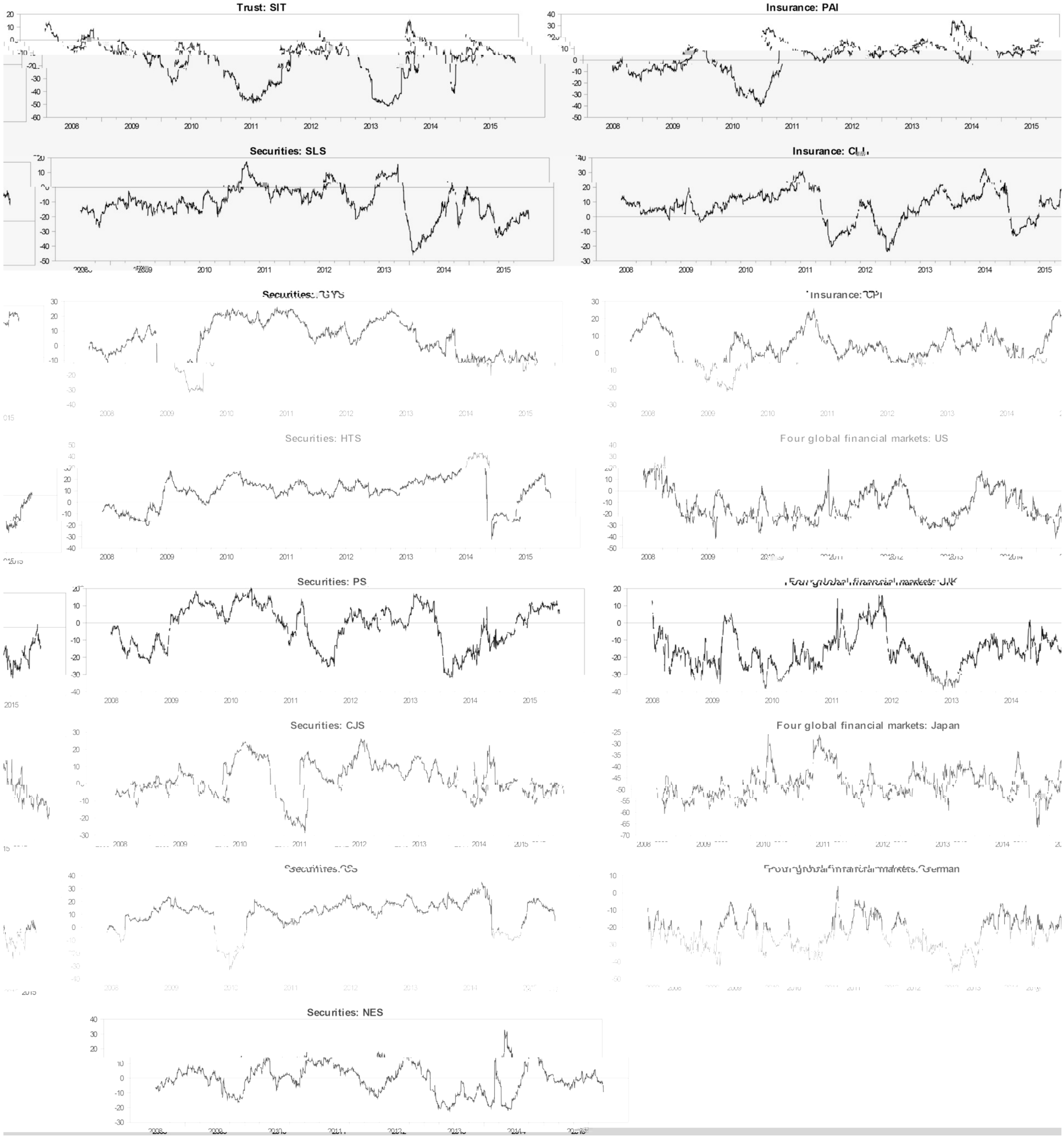

Fig. 1. Dynamic net total directional connectedness, 2008–2015.
A: 11 nonbank financial institutions and 4 global financial sectors
B: 14 banks

conduct further analysis. Before conducting the analysis, we use a 120-trading-day fixed rolling window to extract the total directional connectedness from others, to others, and the net total directional connectedness of each FI using the expanded sample of 32 FIs during 2011–2015. Incorporating more FIs will help facilitate our investigation of the firm-specific determinants. To serve as a further robustness check, as shown in Fig. 4, we verify that the dynamics of net total directional connectedness of the 25 FIs during 2008–2015 and during 2011–2015 are strongly similar, thus confirming again the robustness of the main results above.

Table 6 reports the summary statistics of dynamic total directional connectedness from others, to others, and the net total directional connectedness of the 32 FIs. Again, these summary statistics confirm our previous conclusions: 1) Banks play a central role in the transmission of financial shocks; 2) Nonbank FIs also have a considerable influence in the financial shock transmission network; and 3) Market-oriented commercial banks typically play a more pronounced role than the Big Four in financial shock

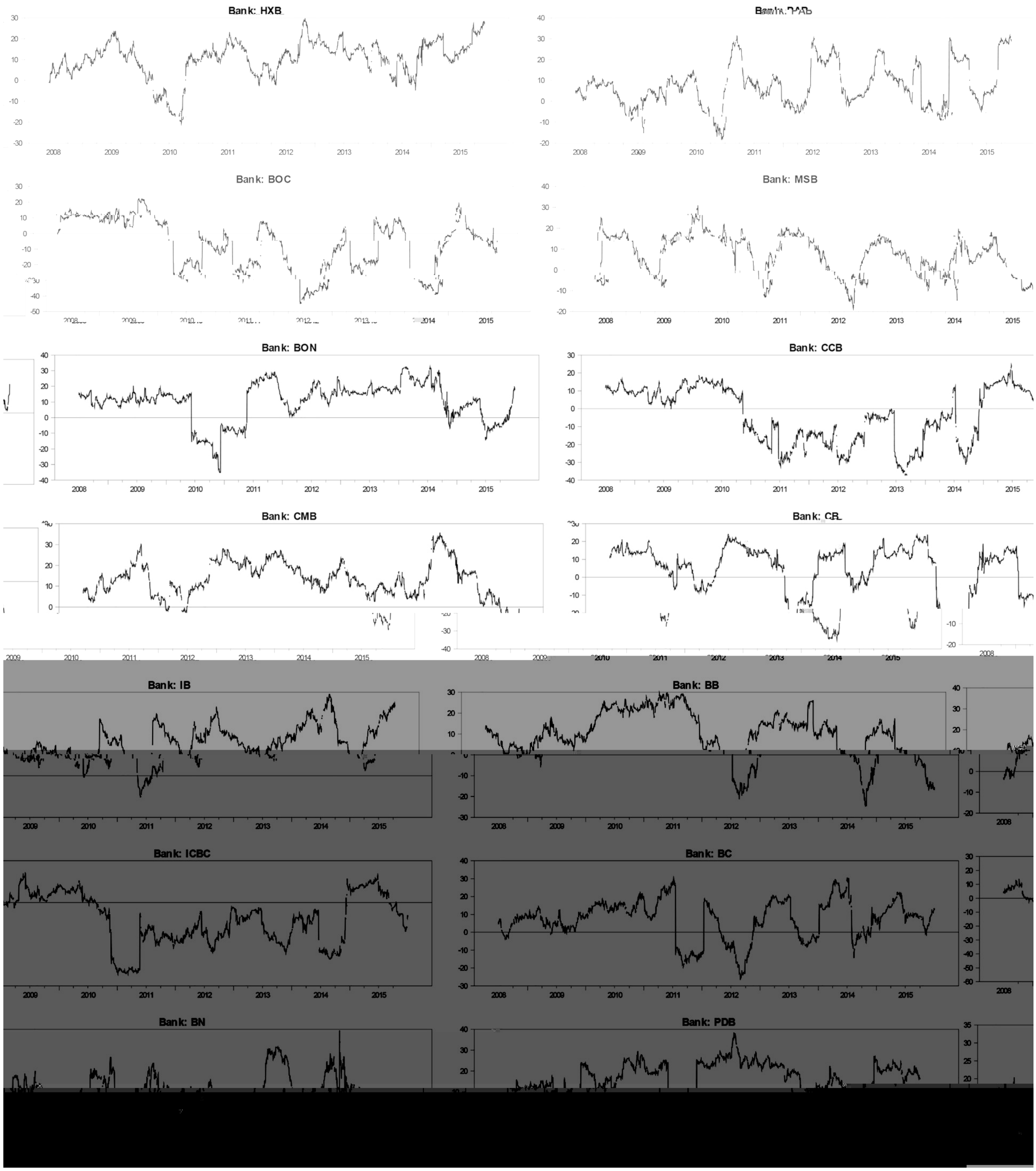

Fig. 1. (*continued*)

transmission network. In the following analysis, we will use the connectedness measured at the end of a month (or quarter) to explore how various factors at monthly (or quarterly) intervals could affect the spillover pattern.

6.2.1. Macroeconomic factors

In this section, we will investigate whether the transmission of financial shocks is influenced by macroeconomic factors. The impact of macroeconomic factors on the performance and risk of FIs can be even more pronounced than firm-specific factors, as suggested by Collin-Dufresne et al. (2001). We will comprehensively examine a number of macroeconomic factors in

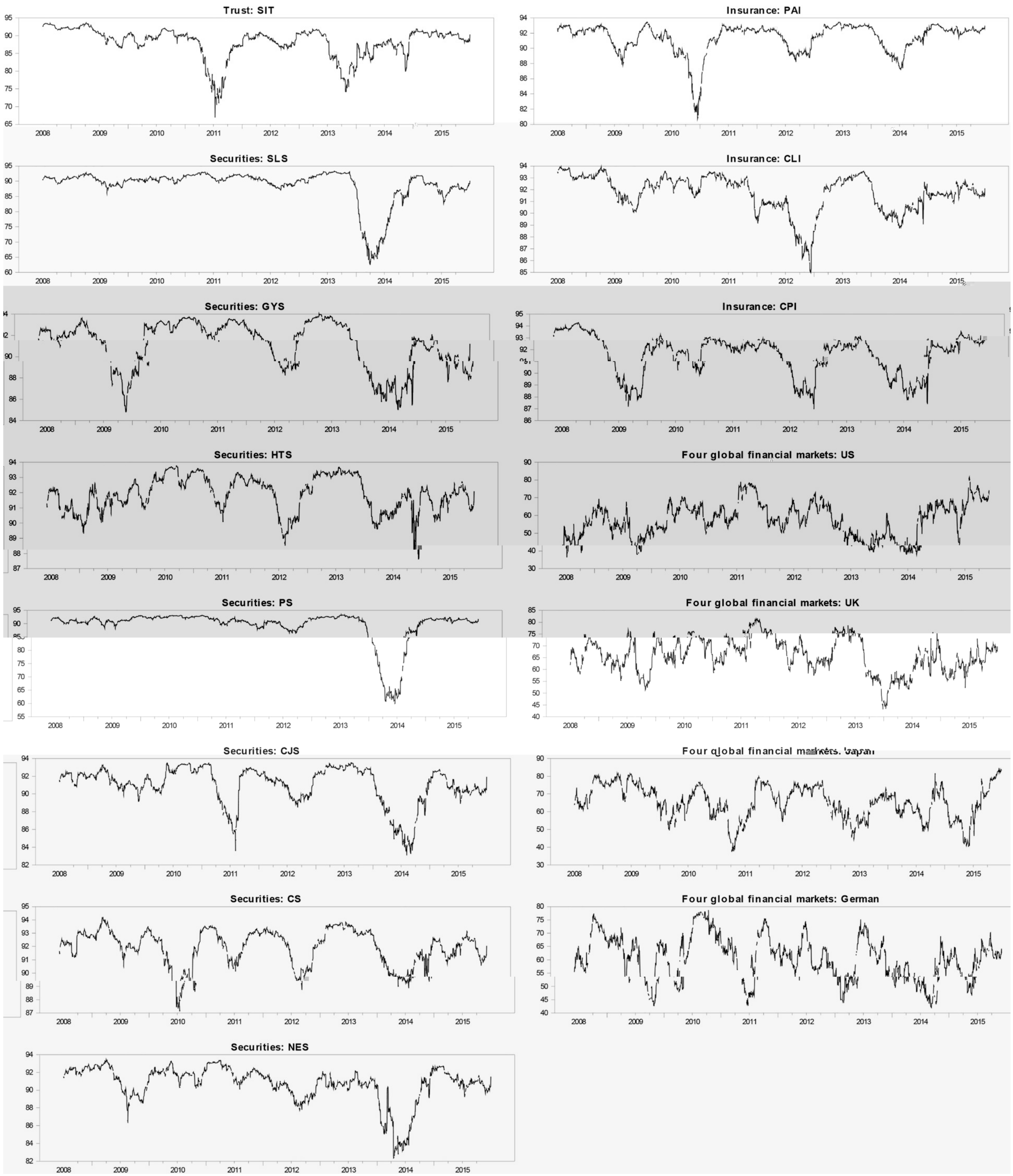

Fig. 2. Dynamic total directional connectedness from others, 2008–2015.
A: 11 nonbank financial institutions and 4 global financial sectors
B: 14 banks

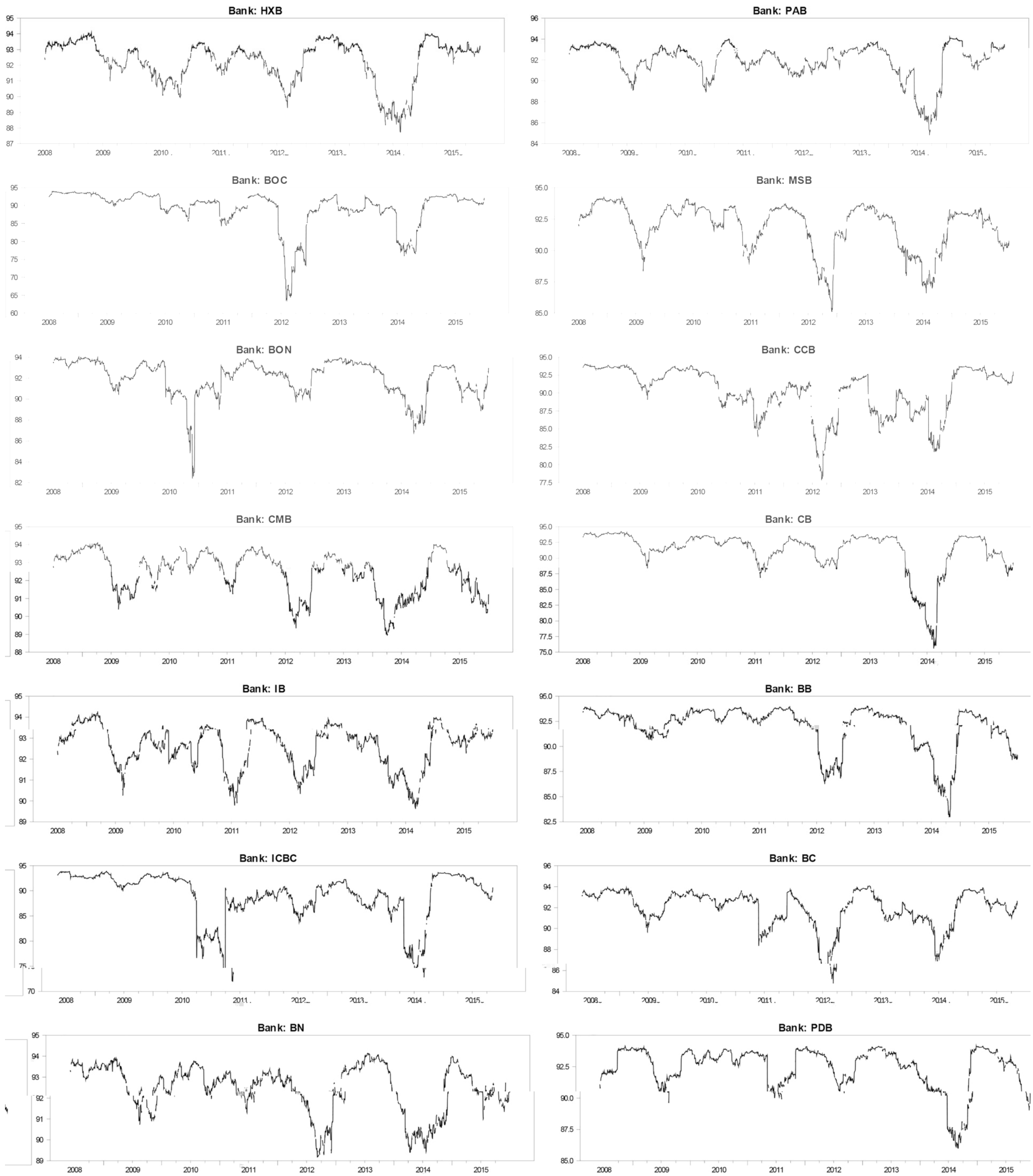

Fig. 2. (*continued*)

China.[17] Following Yang and Zhou (2013), as a preliminary analysis, we will first use a simple regression based on Newey-West robust standard errors to examine whether a certain macroeconomic factor (or various indicators of the same factor) impacts the connectedness (net, from, to) of an FI with both statistical and (at least some) economic significance.[18] Then, based on the results of

[17] All macroeconomic factor variables are collected form the CEIC database.

[18] As a very preliminary prescreening measure, we consider variables with explanatory power equal to or > 1% (i.e., with adjusted-R^2 equal to or > 1%) as meeting the minimum threshold of economic significance.

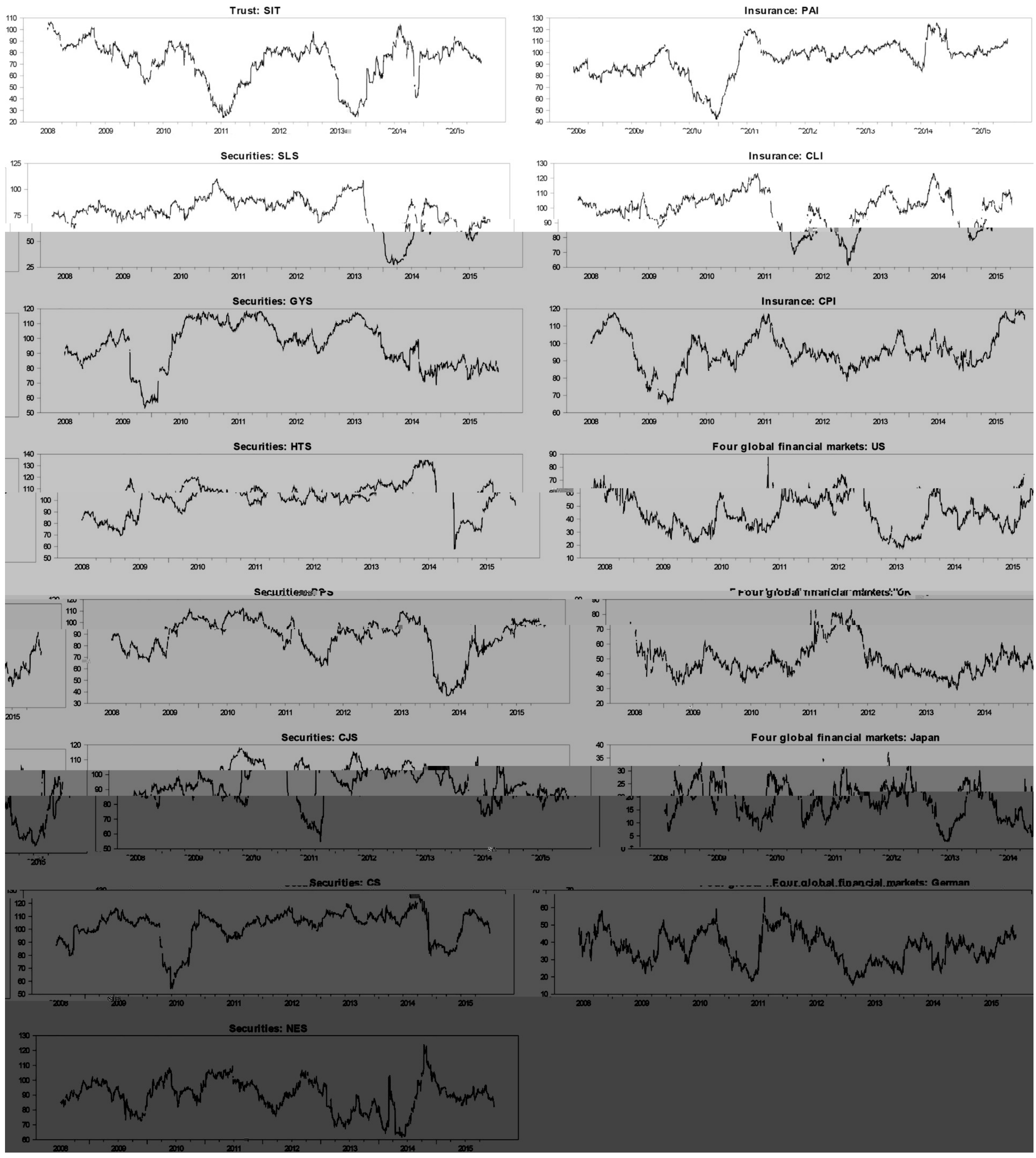

Fig. 3. Dynamic total directional connectedness to others, 2008–2015.
A: 11 nonbank financial institutions and 4 global financial sectors
B: 14 banks

these simple regressions, we will further conduct multiple regressions based on Newey-West robust standard errors to finalize the selection of comparatively important factors, after controlling for collinearity of these factors.

First, we examine whether the transmission of financial shocks is affected by various monetary policy measures. An important monetary measure in China is the money supply, particularly M2 and its various components (quasi money and its three components, i.e., saving deposits, time deposits, and other deposits). As reported in Table 7-A, only quasi money and its component of other deposits impact total directional connectedness from others with both statistical and economic significance (Panel A of Table 7-A). This finding implies that financial shock transmission is affected by M2, mainly through changes in the 'other deposit'

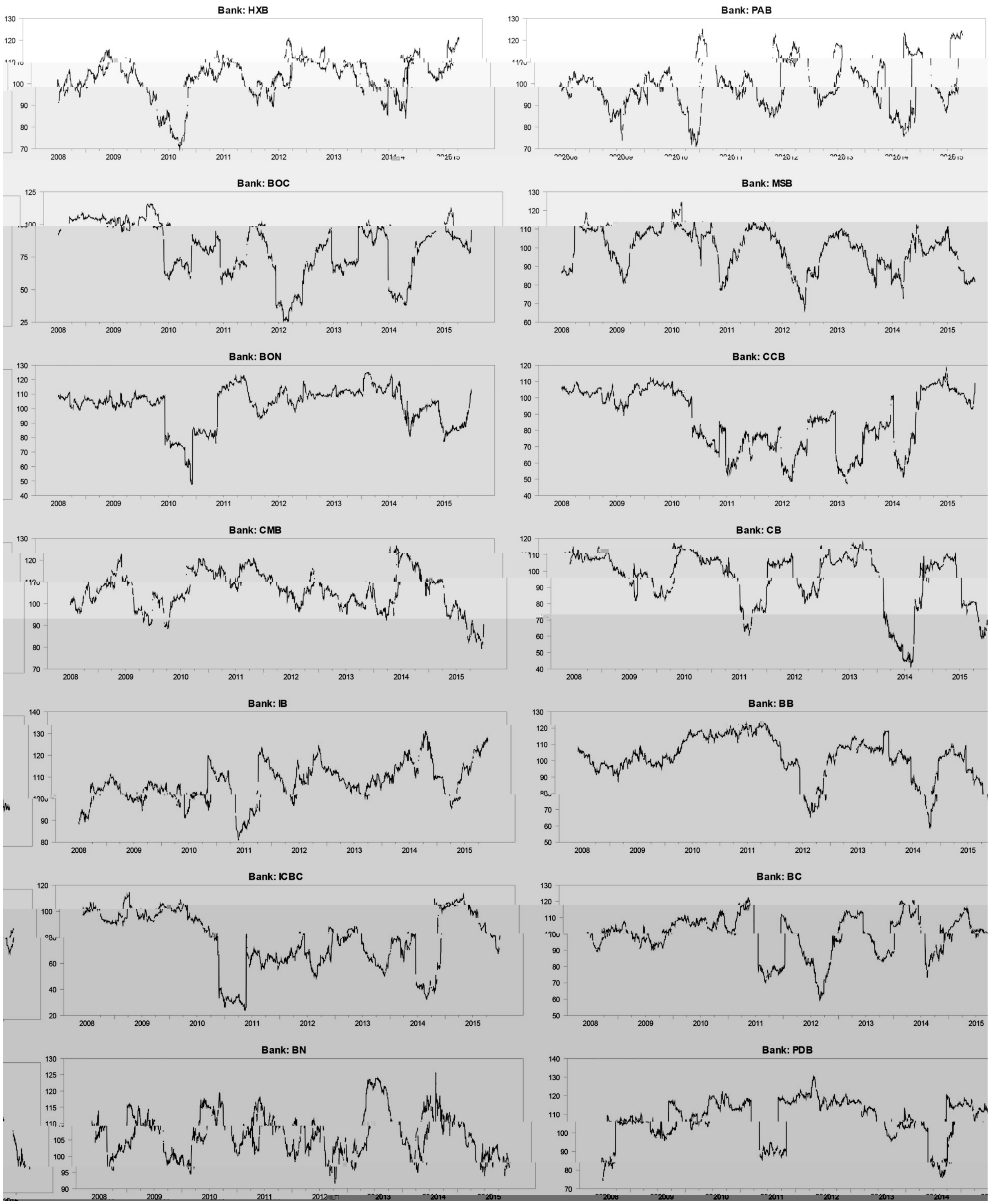

Fig. 3. (*continued*)

component.

Second, with interest rate liberalization, short-term interest rates are also increasingly becoming the monetary policy target in China. We thus examine the role of different money market interest rates, that is, the Shanghai Interbank Offered Rates (SHIBOR), with maturities from overnight to one year. We find that longer-maturity SHIBOR (6-month, 9-month, and 1-year) affect total

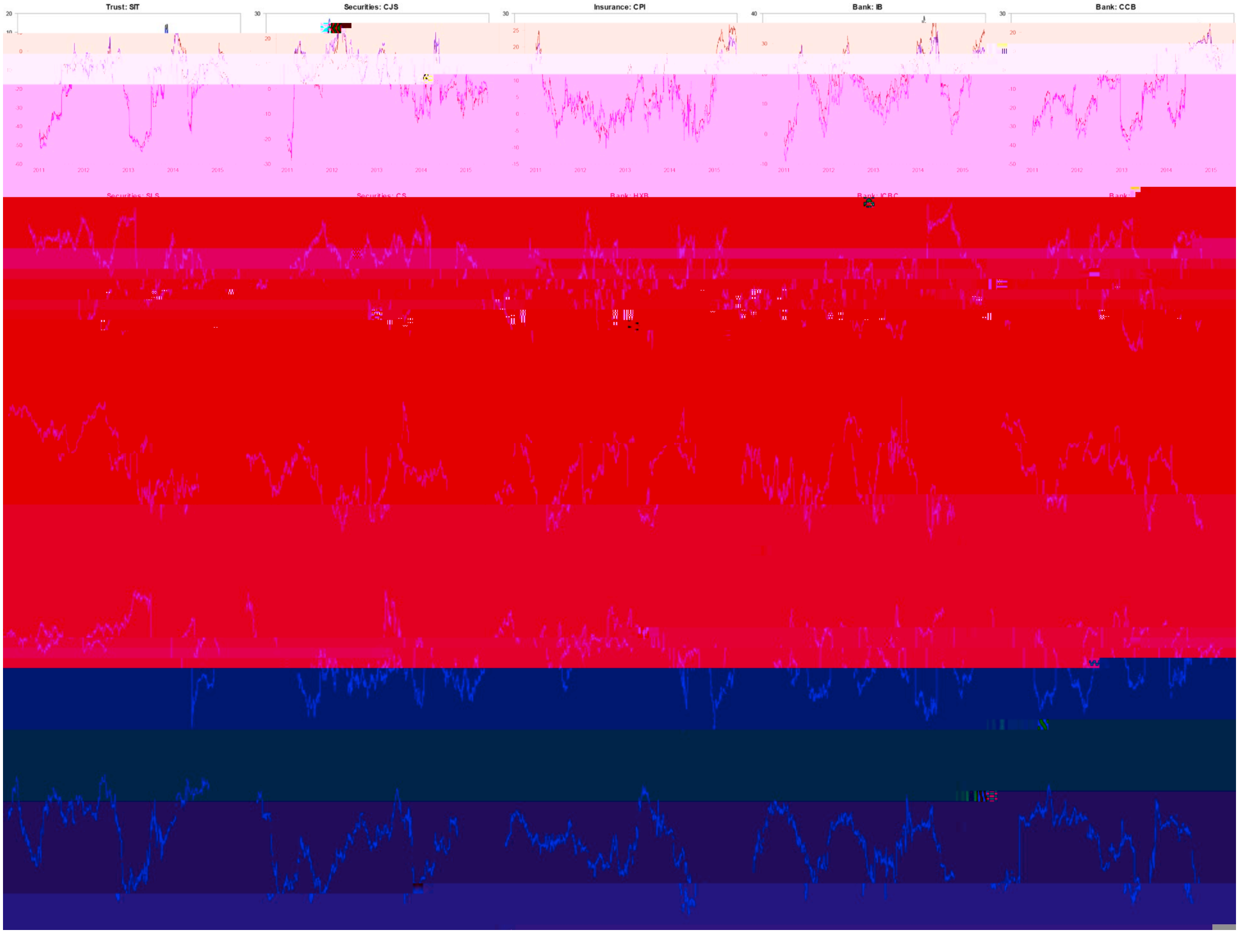

Fig. 4. Net total directional connectedness of 25 financial institutions extracted from 2008 to 2015 and 2011–2015 samples.
Notes: The black line and blue line represent the net total directional connectedness estimated from the 2008–2015 25-financial-institution sample and the 2011–2015 32-financial-institution sample, respectively.

directional connectedness from others with both statistical and economic significance (Panel B of Table 7-A), with longer-maturity SHIBOR having an even more significant impact on financial shock transmission.

Third, we examine whether the transmission of financial shocks is affected by the development of informal financial systems or the shadow banking system in China. These systems have been suggested as potentially destructive factors in China's financial system (e.g., Allen et al., 2012). Due to poor data availability, we used a very limited proxy to examine the three most popular informal finance measures in China. These included emerging Internet finance as measured by Yu'e Bao[19] 7-day annualized return as the proxy, the informal credit market measured by the Wenzhou private lending rate (average, automobile, and real estate mortgage), and the shadow banking system as proxied by deposit and portfolio investments of the insurance sector. We found that the Yu'e Bao 7-day annualized return and the Wenzhou private lending rate (especially for automobile mortgage lending) had both statistically and economically significant impact on the total directional connectedness from others for the transmission of financial shocks (Panel C of Table 7-A).

Fourth, we examine whether the transmission network of financial shocks is affected by the RMB exchange rate with increasing internationalization, as measured by currency swap programs between China and other countries. Years of continuing RMB appreciation and rapid increases in China's foreign exchange reserves suggest there is a large amount of speculative "hot" money, which is a potentially destructive force in China's financial system (Allen et al., 2012). Specifically, we examine the influence of China's real effective exchange rate and different terms of currency swap rates (i.e., one week, one month, three months, six months, nine months, and one year), finding that the real effective exchange rate has both statistically and economically significant impact on the total directional connectedness from others in the transmission network of financial shocks (Panel D of Table 7-A).

Fifth, we examine whether the transmission network of financial shocks is affected by the various Banking Climate Indices (BCIs)

[19] Yu'e Bao is sponsored and managed by Alibaba, the largest Internet commercial company in China, and became the world's largest money market fund in 2017.

Table 6
Summary statistics of estimated dynamic connectedness 2011–2015.

	From				To				Net			
	Mean	Std.D	Min	Max	Mean	Std.D	Min	Max	Mean	Std.D	Min	Max
SIT	0.901	0.035	0.728	0.938	0.713	0.193	0.241	1.037	−0.188	0.164	−0.537	0.121
SLS	0.904	0.055	0.689	0.95	0.798	0.2	0.272	1.118	−0.106	0.155	−0.505	0.172
GYS	0.932	0.015	0.887	0.954	0.998	0.137	0.701	1.214	0.067	0.125	−0.209	0.264
HTS	0.939	0.008	0.892	0.953	1.096	0.133	0.555	1.373	0.157	0.131	−0.381	0.441
PS	0.908	0.059	0.696	0.949	0.872	0.193	0.371	1.124	−0.037	0.143	−0.408	0.178
CJS	0.931	0.016	0.872	0.952	0.989	0.107	0.621	1.198	0.058	0.097	−0.266	0.278
CS	0.94	0.008	0.919	0.953	1.108	0.092	0.803	1.289	0.168	0.092	−0.135	0.35
NES	0.927	0.014	0.875	0.946	0.925	0.11	0.669	1.294	−0.002	0.104	−0.251	0.356
HUAT	0.939	0.009	0.911	0.952	1.103	0.092	0.942	1.359	0.164	0.091	0.001	0.425
GFS	0.937	0.01	0.905	0.951	1.056	0.124	0.813	1.364	0.12	0.121	−0.117	0.426
CMS	0.935	0.011	0.898	0.951	1.055	0.124	0.716	1.371	0.119	0.12	−0.182	0.442
IS	0.933	0.013	0.898	0.949	1.015	0.116	0.683	1.198	0.082	0.109	−0.224	0.271
ES	0.934	0.01	0.901	0.95	1.023	0.103	0.753	1.277	0.089	0.1	−0.165	0.348
PAI	0.934	0.01	0.903	0.947	1.017	0.077	0.875	1.253	0.083	0.075	−0.058	0.322
CLI	0.929	0.012	0.892	0.95	0.961	0.135	0.677	1.244	0.032	0.129	−0.226	0.314
CPI	0.932	0.011	0.899	0.949	0.969	0.076	0.824	1.183	0.038	0.071	−0.105	0.239
Nonbank av.	0.928	0.019	0.860	0.950	0.981	0.126	0.657	1.244	0.053	0.114	−0.236	0.309
Bank av.	0.927	0.020	0.858	0.951	0.951	0.131	0.628	1.212	0.024	0.116	−0.246	0.273
HXB	0.936	0.012	0.902	0.952	1.039	0.079	0.818	1.208	0.103	0.072	−0.092	0.278
BOC	0.905	0.042	0.753	0.947	0.761	0.186	0.329	1.16	−0.144	0.149	−0.443	0.22
BON	0.936	0.012	0.893	0.952	1.06	0.1	0.734	1.242	0.124	0.095	−0.198	0.298
CMB	0.936	0.01	0.908	0.952	1.035	0.103	0.748	1.27	0.098	0.101	−0.176	0.34
IB	0.939	0.009	0.914	0.953	1.086	0.089	0.826	1.283	0.147	0.087	−0.093	0.342
ICBC	0.905	0.033	0.792	0.948	0.723	0.19	0.364	1.145	−0.182	0.162	−0.444	0.198
BN	0.938	0.011	0.908	0.955	1.065	0.081	0.894	1.264	0.127	0.076	−0.042	0.338
PAB	0.933	0.016	0.875	0.953	0.999	0.12	0.718	1.241	0.067	0.109	−0.159	0.303
MSB	0.93	0.016	0.873	0.949	0.945	0.104	0.657	1.136	0.015	0.091	−0.217	0.202
CCB	0.91	0.03	0.798	0.95	0.785	0.18	0.435	1.168	−0.125	0.155	−0.428	0.219
CB	0.921	0.032	0.807	0.951	0.895	0.2	0.424	1.177	−0.026	0.172	−0.393	0.228
BB	0.931	0.019	0.868	0.952	0.983	0.14	0.623	1.248	0.053	0.125	−0.246	0.303
BC	0.931	0.015	0.877	0.952	0.962	0.131	0.666	1.212	0.031	0.121	−0.217	0.284
PDB	0.936	0.015	0.885	0.953	1.052	0.126	0.75	1.28	0.116	0.114	−0.139	0.342
AB	0.912	0.034	0.799	0.947	0.801	0.163	0.392	1.155	−0.111	0.134	−0.418	0.213
EB	0.935	0.016	0.879	0.951	1.03	0.106	0.666	1.2	0.095	0.095	−0.23	0.255

Notes: This table reports the summary statistics of estimated dynamic total directional connectedness from others (From), to others (To), and net total directional connectedness (Net) of 32 financial institutions using a 120-trading-day fixed rolling window. Std.D: standard deviation; av.: average.

constructed by the PBOC. BCIs involve a wide range of macroeconomic activities that are closely related to the operation of banks. BCIs also serve as an important reference for financial regulation and supervision in China. We examine the BCIs for the degree of economic overheating, the industry climate, bankers' confidence, money policy sentiment, profitability, demand for various loans (manufacturing and nonmanufacturing, large, medium, and small and micro enterprises, and so on), and loan approvals. Our findings reveal that only the BCI of money policy sentiment impacts the total directional connectedness from others in the transmission network of financial shocks with both statistical and economic significance (Panel E of Table 7-A).

Sixth, we explore the role of the Chinese real estate market, especially the funding sources of real estate investment. China's booming real estate market, especially its soaring housing prices, has attracted worldwide attention during the past decade. For example, the IMF (2011) lists “potential steep price correction in Chinese property markets” as a major risk to global recovery from the financial crisis. Allen et al. (2012) noted the potentially destructive outcomes for China's financial system if turmoil emerges in the Chinese real estate market. Nevertheless, our findings do not show that real estate market investment affects the transmission network of financial shocks with either statistical or economic significance. Almost all types of real estate investment funding sources (domestic loans, foreign direct investment, self-raised funding, and other funds such as deposits, advanced payment, and mortgage) affect the total directional connectedness from others in the transmission network of financial shocks with statistical but not economic significance (Panel F of Table 7-A).

Lastly, we also examine whether the transmission network of financial shocks is affected by the fiscal budget/surplus, revenue, and expenditures of the central government and local governments, respectively. Since the 1994 tax reform in China, a large portion of local government revenue must be reallocated by the central government. This reallocation induces local governments to depend heavily on land transformation and the so-called financial platform firms to finance their public expenditures. Such local government behaviors are deemed as the hands pushing China's booming real estate market, with potentially destructive effects for China's

Table 7

Macroeconomic factors.

7-A: Simple regressions

	Net			From			To		
	Estimate	Obs.	adj-R^2	Estimate	Obs.	adj-R^2	Estimate	Obs.	adj-R^2
Panel A: Money policy—money supply, M2, year to year growth (%)									
Money supply-M2	0.128	1728	−0.000	−0.046	1728	−0.000	0.082	1728	−0.001
	(0.446)			(0.065)			(0.492)		
M2: Quasi money	−0.132	1728	−0.000	**−0.240***	**1728**	**0.030**	−0.372	1728	0.001
	(0.304)			(0.037)			(0.334)		
M2, Quasi money: saving deposit	−0.078	1728	−0.000	−0.029	1728	0.001	−0.106	1728	−0.000
	(0.203)			(0.031)			(0.227)		
M2, Quasi money: time deposit,	−0.019	1728	−0.001	−0.009	1728	−0.000	−0.027	1728	−0.001
	(0.145)			(0.019)			(0.160)		
M2, Quasi money: other deposit	0.004	1728	−0.001	**−0.019***	**1728**	**0.026**	−0.015	1728	−0.000
	(0.036)			(0.006)			(0.040)		
Panel B: Shanghai Interbank Offered Rates (SHIBOR) (%)									
Overnight	−0.018	1728	−0.001	0.162**	1728	0.003	0.144	1728	−0.001
	(0.563)			(0.075)			(0.619)		
1 week	−0.091	1728	−0.001	0.070	1728	0.000	−0.021	1728	−0.001
	(0.577)			(0.073)			(0.635)		
2 week	−0.106	1728	−0.001	0.059	1728	0.000	−0.046	1728	−0.001
	(0.542)			(0.072)			(0.600)		
1 month	−0.098	1728	−0.001	0.078	1728	0.000	−0.021	1728	−0.001
	(0.578)			(0.074)			(0.639)		
3 month	−0.389	1728	−0.000	−0.240*	1728	0.005	−0.629	1728	0.000
	(0.810)			(0.125)			(0.906)		
6 month	−0.684	1728	0.000	**−0.540***	**1728**	**0.018**	−1.224	1728	0.002
	(1.036)			(0.153)			(1.147)		
9 month	−0.749	1728	0.000	**−0.720***	**1728**	**0.027**	−1.469	1728	0.002
	(1.123)			(0.163)			(1.242)		
1 year	−0.764	1728	0.000	**−0.779***	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
	(1.175)			(0.163)			(1.295)		
Panel C: Informal financial sectors: Internet finance, folk credit market, shadow banking system									
Yu'e Bao 7-day anualized return (%)	−0.333	992	−0.001	**−0.522779***					

Table 7 (*continued*)

7-A: Simple regressions

	Net			From			To		
	Estimate	Obs.	adj-R^2	Estimate	Obs.	adj-R^2	Estimate	Obs.	adj-R^2
BCI: bankers' condifence	−0.002	1728	−0.001	0.003	1728	−0.000	0.001	1728	−0.001
	(0.063)			(0.009)			(0.070)		
BCI: money policy sentiment	0.008	1728	−0.001	**0.059*** **	**1728**	**0.047**	0.067	1728	0.001
	(0.071)			(0.011)			(0.079)		
BCI: Profitability	−0.041	1728	−0.000	−0.021**	1728	0.003	−0.062	1728	0.000
	(0.084)			(0.010)			(0.091)		
BCI: loan demand	−0.039	1728	−0.000	−0.001	1728	−0.001	−0.040	1728	−0.000
	(0.091)			(0.012)			(0.100)		
BCI: loan demand, manufacturing	−0.047	1728	−0.000	−0.002	1728	−0.001	−0.048	1728	−0.000
	(0.093)			(0.012)			(0.102)		
BCI: loan demand, non-manufacturing	−0.062	1728	−0.000	0.000	1728	−0.001	−0.062	1728	−0.000
	(0.164)			(0.021)			(0.180)		
BCI: loan demand, large enterprise	−0.119	1728	0.000	−0.006	1728	−0.001	−0.126	1728	0.000
	(0.209)			(0.028)			(0.230)		
BCI: loan demand, medium enterprise	−0.049	1728	−0.000	−0.003	1728	−0.001	−0.052	1728	−0.000
	(0.109)			(0.014)			(0.119)		
BCI: loan demand, small and micro enterprise	−0.045	1728	−0.000	−0.012	1728	0.001	−0.057	1728	−0.000
	(0.093)			(0.011)			(0.101)		
BCI: loan approval	0.100	1728	−0.000	0.055*	1728	0.005	0.156	1728	0.000
	(0.230)			(0.032)			(0.256)		
Panel F: Real Estate market: real estate climate and real estate investment (REI)									
Real estate climate (index, 2000 = 100)	−0.100	1728	−0.000	0.052	1728	0.001	−0.048	1728	−0.001
	(0.323)			(0.043)			(0.357)		
REI: domestic loans, RMB mn (log-)	0.313	1728	−0.000	−0.516***	1728	0.009	−0.203	1728	−0.001
	(1.086)			(0.159)			(1.202)		
REI: foreign invesment, RMB mn (log-)	−0.050	1728	−0.001	−0.145	1728	0.001	−0.194	1728	−0.001
	(0.832)			(0.156)			(0.948)		
REI: foreign invesment, direct invesmtne, RMB mn (log-)	−0.040	1728	−0.001	−0.154	1728	0.001	−0.194	1728	−0.001
	(0.833)			(0.155)			(0.949)		
REI: self raised, RMB mn (log-)	0.186	1728	−0.001	−0.391***	1728	0.007	−0.204	1728	−0.001
	(0.864)			(0.142)			(0.965)		
REI: self raised, self owned, RMB mn (log-)	0.100	1728	−0.001	−0.414***	1728	0.008	−0.314	1728	−0.001
	(0.850)			(0.146)			(0.954)		
REI: other funds, RMB mn (log-)	0.262	1728	−0.000	−0.276**	1728	0.004	−0.014	1728	−0.001
	(0.787)			(0.126)			(0.877)		
REI: other funds, deposits & advanced payment, RMB mn (log-)	0.260	1728	−0.000	−0.292**	1728	0.005	−0.033	1728	−0.001
	(0.774)			(0.124)			(0.863)		
REI: other funds, mortgage, RMB mn (log-)	0.326	1728	−0.000	−0.242*	1728	0.003	0.084	1728	−0.001
	(0.810)			(0.124)			(0.898)		
Panel G: Government surplus, revenue, and expenditure (RMB bn, log-)									
Government surplus	0.073	1728	−0.001	−0.266**	1728	0.001	−0.193	1728	−0.001
	(0.712)			(0.120)			(0.793)		
Government revenue	1.420	1728	−0.000	0.383	1728	0.000	1.803	1728	−0.000
	(2.327)			(0.379)			(2.604)		
Government expenditure	0.543	1728	−0.000	0.545***	1728	0.004	1.088	1728	−0.000
	(1.205)			(0.154)			(1.321)		
Central government surplus	−0.015	1664	−0.001	−0.392***	1664	0.003	−0.406	1664	−0.001
	(0.682)			(0.100)			(0.755)		
Central government revenue	0.688	1664	−0.000	−0.208	1664	−0.000	0.481	1664	−0.001
	(1.325)			(0.213)			(1.479)		
Central government expenditure	1.086	1664	−0.000	0.665**	1664	0.003	1.751	1664	−0.000
	(1.910)			(0.262)			(2.098)		
Local government surplus	0.068	1664	−0.001	−0.358**	1664	0.001	−0.290	1664	−0.001
	(0.979)			(0.182)			(1.105)		
Local government revenue	1.502	1664	−0.000	0.736*	1664	0.003	2.238	1664	0.000
	(2.486)			(0.388)			(2.776)		
Local government expenditure	0.611	1664	−0.000	0.659***	1664	0.007	1.270	1664	0.000
	(1.153)			(0.151)			(1.266)		

(*continued on next page*)

financial system (Allen et al., 2012). Nevertheless, our study results do not reveal that any of these related variables are economically significant (Panel G of Table 7-A).

Based on the above results of simple regressions, we further perform a set of multiple variable robust regressions to determine the comparatively important factors, as many of these factors may be related to one another. Table 7-A reports the results, showing that only monetary policy-related factors (i.e., other deposits of quasi money in M2 [negative], 1-year SHIBOR [negative], and real effective exchange rates [positive]) have both statistically and economically significant explanatory power for the total directional connectedness from others. However, these factors have neither statistical nor economic significant influence on either total directional connectedness to others or the net total directional connectedness. Hence, there are macroeconomic factors, especially monetary policy measures, which determine the degree of influence by others in the transmission network of financial shocks.

6.2.2. *Firm-specific determinants*

In the following sections, we will investigate whether and how the transmission of financial shocks in China is influenced by firm-specific factors, as commonly discussed in the literature (e.g., Chen et al., 2010; Li et al., 2019). First, we examine the influence of leverage ratios (i.e., total debt to total assets, long-term debt to total assets, and short-term debt to total assets). Yang and Zhou (2013) also find that the short-term debt ratio is one of the significant determinants a□ecti fUies, v0j,NsÙil NoversOGfIfj0j,N t mmonCi X) asseto rati ?s lose(sta,j significance.

global systemically important financial institutions (G-SIFIs). Furthermore, size has been widely used to detect G-SIFIs or SIFIs for the purposes of financial regulation and supervision (IMF, BIS, and FSB, 2009; Allahrakha et al., 2015; Glasserman and Loudis, 2015). Therefore, larger FIs may have been under stricter supervision given the “too big to fail” belief prevalent since the 2008 financial crisis. This may have forced larger FIs to be more conservative in their business activities, thus reducing their potential risk spillovers. Such a mechanism surely may have occurred in China, as the government made substantial efforts to solve the problem of NPLs among the Big Four even during the late 1990s.

Fourth, we examine whether the transmission of financial shocks is affected by FI profitability as measured by net operational cash flow per share. To a certain extent, net operational cash flow per share can be considered a proxy for profitability. Better profitability will surely attract more market attention, resulting in a significant positive influence of net operational cash flow per share on total directional connectedness from others and to others, as well as net total directional connectedness during the transmission of financial shocks. For further confirmation, we also examine the influence of basic profit ratio per share, finding that it has a similar but even stronger influence pattern than net operational cash flow per share. Concerning the profit structure, we find that both financial profit and operating profit ratios negatively affect the roles of FIs in the shock transmission network. However, only the operating profit ratio is statistically significant.

Fifth, we further examine the role of FI asset tangibility. Specifically, we explore the ratios of the intangible assets to total assets and tangible assets to total assets. We document that the intangible (tangible) asset ratio negatively (positively) affects the roles of FIs in the shock transmission network (net, from, and to).

Finally, among the individually significant factors based on simple regressions, we conduct multiple regressions with Newey-West robust standard errors to select the more important factors at the 10% significance level.[21] In the first set of multiple regressions, we include accounts receivable turnover, but not the short-term debt to total assets and liquid assets to total assets ratios due to concerns of collinearity. Although we can only obtain preliminary results from 44 observations, the findings suggest that accounts receivable turnover may not be as important as it was in the simple regression. In particular, the estimated coefficients lose their statistical significance and the adjusted R^2 turns out to be comparatively lower (Columns 1–3 of Table 8-B). Then, we conduct another set of

Table 8
Firm-specific factors.

8-A: Simple regressions

	Net			From			To		
	Estimate	Obs.	Adj-R^2	Estimate	Obs.	Adj-R^2	Estimate	Obs.	Adj-R^2
Total debt to total asset	0.054	576	0.003	0.014	576	0.012	0.068	576	0.005
	(0.058)			(0.009)			(0.065)		
Long-term debt to total asset	0.100*	483	0.018	0.018*	483	0.020	0.118*	483	0.020
	(0.054)			(0.009)			(0.061)		
Short-term debt to total asset	−1.382***	483	0.061	−0.118**	483	0.014	−1.500***	483	0.057
	(0.324)			(0.056)			(0.377)		
Accounts receivable turnover	−0.001***	144	0.150	−0.000**	144	0.031	−0.002***	144	0.142
	(0.000)			(0.000)			(0.000)		
Liquidity asset to total asset	−0.739***	483	0.069	−0.067**	483	0.018	−0.807***	483	0.065
	(0.193)			(0.031)			(0.222)		
Currency asset to total asset	0.059	576	0.004	0.004	576	−0.001	0.063	576	0.004
	(0.042)			(0.007)			(0.047)		
Receivable asset to total asset	0.844	576	0.003	0.088**	576	0.000	0.932	576	0.003
	(0.546)			(0.039)			(0.568)		
Size$_{\text{(market value, RMB, log-)}}$	−0.016**	576	0.020	−0.000	576	−0.001	−0.017*	576	0.017
	(0.008)			(0.001)			(0.009)		
Net operational cash flow per share	0.003***	399	0.032	0.000***	399	0.011	0.004***	399	0.030
	(0.001)			(0.000)			(0.001)		
Basic profit ratio per share	0.044***	576	0.036	0.007***	576	0.034	0.050***	576	0.039
	(0.009)			(0.002)			(0.011)		
Profit generated by financial activities to total profit	−0.003	576	−0.002	−0.000	576	−0.002	−0.003	576	−0.002
	(0.008)			(0.001)			(0.009)		
Operational profit to total profit	−0.250***	576	0.002	−0.007	576	−0.002	−0.257**	576	0.002
	(0.096)			(0.011)			(0.102)		
Intangible asset to total asset	7.088**	576	0.006	0.725*	576	0.001	7.813**	576	0.006
	(3.293)			(0.395)			(3.559)		
Tangible asset to total asset	−4.502***	576	0.019	−0.406***	576	0.005	−4.908***	576	0.018
	(1.038)			(0.139)			(1.095)		

8-B: Multiple regressions

	Dependent variables					
	(1)	(2)	(3)	(4)	(5)	(6)
	Net	From	To	Net	From	To
Long-term debt to total asset	−0.061	0.034	−0.027	−0.058	−0.010	−0.068
	(0.280)	(0.058)	(0.327)	(0.092)	(0.009)	(0.099)
Short-term debt to total asset				−1.079***	−0.090*	−1.169***
				(0.390)	(0.046)	(0.435)
Accounts receivable turnover	−0.001	0.000	−0.001			
	(0.001)	(0.000)	(0.001)			
Liquidity asset to total asset				−0.473***	−0.060***	−0.532***
				(0.169)	(0.018)	(0.181)
Size $_{\text{(market value, RMB, log-)}}$	0.007	0.002	0.009	−0.032***	−0.003**	−0.035***
	(0.024)	(0.004)	(0.026)	(0.009)	(0.001)	(0.010)
Net operational cash flow per share	(0.002)	(0.000)	(0.002)	(0.001)	(0.000)	(0.001)
	0.024	0.000	0.024	0.044***	0.006***	0.050***
Basic profit ratio per share	(0.016)	(0.002)	(0.016)	(0.013)	(0.002)	(0.015)
	1.316	−0.664	0.652	0.071	0.018	0.089
Operational profit to total profit	(3.504)	(0.644)	(3.960)	(0.392)	(0.043)	(0.419)
	−4.095**	−0.323	−4.418*	−1.387	−0.007	−1.394
Tangible asset to total asset	(2.001)	(0.390)	(2.261)	(2.379)	(0.232)	(2.565)
	2.675	1.836*	4.510	2.199	1.000***	3.199
Constant	(5.109)	(0.917)	(5.783)	(2.472)	(0.242)	(2.663)
	(5.196)	(0.907)	(5.896)	(2.532)	(0.244)	(2.727)
Observations	44	44	44	306	306	306
Adj-R^2	0.128	−0.096	0.097	0.185	0.089	0.182

Notes: This table reports the results of multiple regressions with robust standard errors. The heteroscedasticity and autocorrelation consistent standard errors (HAC) are in parentheses. "*", "**", and "***" denote significance at 10%, 5%, and 1%, respectively.

Chief Economist at the Research Bureau of PBOC, whose hospitality is greatly acknowledged. Jun Ma is also a member of the PBOC monetary policy committee. An earlier abridged version of this paper was published in Chinese as a PBOC working paper (No. 2017-4), titled "Transmission of Financial Shocks among Chinese Financial Institutions: A Global Perspective" in which Yandong Jia also participated. The views expressed in this paper are those of the authors and do not reflect the official positions of PBOC. Yang acknowledges the support of the National Natural Science Foundation of China (71571106). Yu acknowledges financial support from the Fundamental Research Funds for the Central Universities (No. 63182068). The project is also supported by the National Social Science Foundation of China (11&ZD016).

Appendix A

Table A-1
Full sample connectedness table with US, UK, and Germany as the leading markets, 2008–2015.

	SIT	SLS	GYS	HTS	PS	CJS	CS	NES	PAI	CLI	CPI	HXB	BOC	BON	CMB	IB	ICBC	BN	PAB	MSB	CCB	CB	BB	BC	PDB	USF	UKF	JPF	GMF	FROM
SIT	10.8	4.2	5.4	4.8	5.1	5.4	4.9	5.3	3.5	3.7	3.9	3.3	2.3	3.5	2.9	3.3	2.3	3.9	3.4	2.9	2.6	2.8	3.1	2.9	3	0.1	0.1	0.3	0.1	89
SLS	4.3	11.1	6.6	5.9	6.1	6.3	5.9	6.3	3.4	3.7	3.6	2.6	2.1	3.1	2.6	2.9	2	3.3	2.9	2.4	2.3	2.5	2.6	2.4	2.7	0.1	0.1	0.3	0.1	89
GYS	4.6	5.5	9.2	5.9	5.8	6.5	5.8	6.4	3.5	3.7	3.8	2.8	2.2	3.2	2.7	3	2.2	3.5	3	2.6	2.6	2.5	2.7	2.6	2.8	0.1	0.1	0.2	0.1	91
HTS	4	4.8	5.7	8.9	5.3	6.2	6.6	5.6	3.5	3.8	4	3.2	2.3	3.2	3	3.3	2.3	3.4	3.2	2.8	2.7	2.8	3.1	2.8	3.1	0	0	0.3	0	91
PS	4.7	5.4	6.2	5.8	9.8	6.2	5.9	6	3.4	3.7	3.6	3	2.3	3.2	2.8	2.9	2.3	3.4	3	2.5	2.7	2.6	2.8	2.7	2.8	0.1	0.1	0.3	0.1	90
CJS	4.4	5.1	6.3	6.2	5.7	8.9	6.2	6.3	3.3	3.7	3.6	3	2.2	3.2	2.7	3.1	2.2	3.5	3.1	2.7	2.6	2.6	2.9	2.8	3	0.1	0.1	0.3	0.1	91
CS	3.8	4.4	5.2	6.1	5	5.8	8.3	5.3	3.8	4.2	4.1	3.3	2.4	3.2	3.2	3.5	2.4	3.5	3.4	2.9	2.9	3	3	3	3.5	0.1	0.1	0.4	0.1	92
NES	4.6	5.4	6.5	5.9	5.8	6.7	5.9	9.4	3.4	3.6	3.7	2.9	2.3	3.1	2.7	3	2.1	3.5	3.1	2.6	2.6	2.6	2.8	2.6	2.9	0.1	0.1	0.2	0.1	91
PAI	2.7	2.6	3.2	3.3	2.9	3.2	3.9	3.1	8.4	5.7	5.9	4	3.2	3.6	4.3	4.2	3.2	3.7	4.1	3.8	3.9	3.4	3.8	4.2	3.9	0.4	0.3	0.8	0.2	92
CLI	2.9	2.7	3.4	3.5	3.1	3.4	4.1	3.2	5.6	8.2	6	3.9	3.5	3.6	4.1	3.9	3.4	3.8	3.7	3.9	3.9	3.6	3.6	4.1	3.7	0.2	0.1	0.6	0.1	92
CPI	3	2.6	3.4	3.7	3.1	3.4	4	3.2	5.7	6	8.2	4	3.3	3.7	4.1	4	3.2	3.9	3.8	3.8	3.8	3.5	3.9	4.1	3.7	0.2	0.2	0.6	0.1	92
HXB	2.4	1.8	2.4	2.8	2.4	2.6	3.1	2.4	3.6	3.6	3.7	7.6	3.9	4.7	5.3	5.3	3.8	4.8	4.9	5	4.3	4.4	4.9	4.7	5.1	0.1	0.1	0.3	0.1	92
BOC	2	1.7	2.2	2.4	2.2	2.3	2.7	2.2	3.5	3.8	3.6	4.6	9.1	4	4.7	4.4	5.8	4.5	4.1	4.7	6	4.9	4.3	5.5	4	0.1	0.1	0.4	0.1	91
BON	2.5	2.2	2.8	2.8	2.6	2.8	3.1	2.6	3.4	3.5	3.6	4.9	3.5	7.9	4.6	5	3.8	5.7	4.6	4.4	4.1	4.2	5.3	4.5	4.7	0.1	0.1	0.4	0.1	92
CMB	2.1	1.8	2.3	2.6	2.2	2.4	3	2.2	3.9	3.8	3.8	5.3	3.9	4.5	7.7	5.3	4.1	4.5	4.8	5	4.5	4.2	4.8	4.9	5.2	0.2	0.1	0.6	0.1	92
IB	2.3	1.9	2.4	2.8	2.3	2.6	3.2	2.4	3.7	3.5	3.7	5.2	3.6	4.7	5.2	7.5	3.7	4.9	5.3	4.9	4.1	4.2	5	4.6	5.5	0.1	0.1	0.4	0.1	93
ICBC	2	1.7	2.2	2.4	2.2	2.3	2.6	2.1	3.5	3.8	3.6	4.6	5.8	4.4	4.9	4.5	9.2	4.2	4.1	4.7	6.1	4.4	4.3	5.5	4.2	0.1	0.1	0.5	0.1	91
BN	2.8	2.3	2.9	2.9	2.7	3	3.2	2.8	3.3	3.5	3.6	4.8	3.8	5.5	4.4	4.9	3.5	7.6	4.7	4.4	4	4.7	5.1	4.6	4.5	0.1	0.1	0.3	0	92
PAB	2.5	2.1	2.6	2.8	2.4	2.8	3.2	2.6	3.8	3.6	3.6	5	3.5	4.5	4.9	5.6	3.5	4.9	7.8	4.9	4.1	4.2	4.7	4.6	5.2	0.1	0.1	0.4	0	92
MSB	2.2	1.8	2.3	2.6	2.1	2.4	2.8	2.3	3.6	3.8	3.8	5.3	4.1	4.5	5.2	5.3	4.1	4.7	5	8	4.5	4.5	4.7	5	4.9	0.1	0.1	0.4	0.1	92
CCB	2	1.7	2.3	2.5	2.3	2.4	2.9	2.3	3.8	3.9	3.8	4.7	5.4	4.2	4.8	4.5	5.5	4.3	4.3	4.7	8.2	4.5	4.4	5.4	4.2	0.2	0.2	0.5	0.1	92
CB	2.3	1.9	2.3	2.7	2.3	2.5	3	2.4	3.4	3.7	3.6	4.9	4.6	4.5	4.7	4.8	4	5.2	4.6	4.8	4.6	8.5	4.8	5	4.2	0.1	0.1	0.4	0.1	92
BB	2.3	1.9	2.4	2.8	2.3	2.6	2.9	2.4	3.6	3.5	3.8	5.1	3.7	5.2	4.9	5.3	3.7	5.4	4.7	4.6	4.3	4.5	7.9	4.8	4.9	0.1	0.1	0.4	0	92
BC	2.1	1.7	2.2	2.5	2.2	2.4	2.8	2.1	3.9	3.8	3.9	4.9	4.7	4.4	5	4.8	4.6	4.7	4.5	4.8	5.1	4.6	4.7	7.8	4.7	0.2	0.2	0.6	0.1	92
PDB	2.2	2	2.4	2.8	2.4	2.7	3.3	2.4	3.7	3.5	3.6	5.3	3.5	4.7	5.4	5.7	3.6	4.6	5.2	4.8	4.1	3.9	4.9	4.7	7.9	0.2	0.1	0.5	0.1	92
USF	0.4	0.4	0.5	0.2	0.3	0.5	0.5	0.3	2.4	1.3	1	0.5	0.7	0.6	1.1	0.8	0.8	0.4	0.7	0.8	1	0.7	0.6	1.4	0.9	47.6	15.4	9.3	9.1	52
UKF	0.8	0.3	0.6	0.4	0.5	0.6	0.8	0.5	2.8	1.8	1.8	1.3	1.1	1.1	1.9	1.6	1.3	1.2	1.2	1.6	1.6	1.1	1.2	2.1	1.8	13.6	32.4	9.9	12.8	68
JPF	0.9	0.9	1	1.2	1.2	1.3	1.7	0.9	3.7	2.6	2.5	1.7	1.7	2	2.9	2.1	1.9	1.6	1.9	1.8	2.4	1.7	1.8	2.8	2.2	7.2	6.2	37.2	3.2	63
GMF	0.8	0.3	0.7	0.5	0.5	0.7	0.9	0.6	2.7	2	1.7	1.2	0.9	1	1.8	1.5	1.2	1	1	1.3	1.2	1	1.3	1.8	1.6	10.5	15.1	7.6	37.4	63
TO	74	71	88	91	83	92	99	86	102	101	101	105	86	101	107	108	87	106	103	100	99	94	101	106	103	35	40	37	27	**TC =**
NET	− 15	− 18	− 3	0	− 7	1	7	− 5	10	9	9	13	− 5	9	15	15	− 4	14	11	8	7	2	9	14	11	− 17	− 28	− 26	− 36	**87.3**

Notes: This table reports the full sample connectedness calculated from 10-step-ahead generalized forecast error variance decomposition while modeling the US, UK, and German financial sectors as the leading markets. TC, From, TO, and NET denote *total connectedness*, *total directional connectedness from others*, *total directional connectedness to others*, and *net total directional connectedness*, respectively. USF, UKF, JPF, and GMF represent the US financial market, UK financial market, Japanese financial market, and German financial market, respectively.

Appendix B

Table A-2
Full sample connectedness of 32 financial institutions and 4 major global financial sectors 2011–2015.

PAI	2.9	2.7	2.5	3	3	3.1	0.2	0.3	0.2	0.1	3.2	3.2	3.1	2.8	2.8	2.6	3.2	93
CLI	2.9	2.7	2.5	2.9	3.1	2.9	0.1	0.2	0.2	0.1	3.2	3	3	2.8	2.8	2.6	3.2	93
CPI	2.8	2.7	2.3	3	3	2.9	0.1	0.3	0.2	0.1	3.2	3.1	3.1	3	2.9	2.6	3	93
HXB	4	3.5	3.4	4	3.9	4.2	0.2	0.3	0.2	0.1	2.5	2.2	2.4	2	2.2	3.3	4.2	94
BOC	3.5	5.4	4.1	3.5	5.2	3.3	0	0.1	0.1	0	2.1	1.6	1.8	1.5	1.7	6	5.1	91
BON	3.4	3	3.1	3.9	3.5	3.9	0.1	0.2	0.1	0.1	2.7	2.5	2.8	2.4	2.6	2.9	3.9	93
CMB	4.1	3.4	3.3	4	4	4.4	0.2	0.3	0.2	0.1	2.4	2.1	2.4	1.9	2	3.4	4	93
IB	4.1	3	3.3	4	3.7	4.5	0.2	0.3	0.1	0.1	2.6	2.3	2.5	2.2	2.3	3.2	4	94
ICBC	3.7	5.4	3.2	3.4	4.8	3.4	0.1	0.2	0.2	0.1	2.2	1.8	2.1	1.7	1.8	5.7	4.5	91
BN	3.2	2.9	3.3	3.8	3.7	3.7	0.1	0.2	0.1	0.1	2.7	2.5	2.7	2.4	2.7	3	4	94
PAB	3.9	2.8	3.2	3.7	3.5	4.1	0.1	0.2	0.1	0.1	2.7	2.6	2.8	2.3	2.6	3	3.7	93
MSB	7.5	3.5	3.5	3.9	4	4.4	0.1	0.2	0.1	0.1	2.2	1.9	2.2	1.8	2	3.6	4.1	92
CCB	3.6	7.7	3.3	3.5	4.7	3.4	0.1	0.3	0.1	0.1	2.3	2	2.2	1.7	2.1	5.3	4.5	92
CB	3.8	3.5	8.2	3.9	4.2	3.7	0.1	0.2	0.1	0.1	2.3	2.1	2.2	1.9	2.1	3.6	4.9	92
BB	3.7	3.2	3.4	7.1	3.9	4.2	0.2	0.2	0.1	0.1	2.3	2.2	2.4	2.1	2.2	3.2	4.2	93
BC	3.6	4.1	3.5	3.8	6.9	3.8	0.1	0.2	0.2	0	2.4	2.1	2.3	1.9	2.1	4.3	4.8	93
PDB	4	3	3.1	4	3.8	6.8	0.2	0.3	0.2	0.1	2.6	2.3	2.5	2.1	2.3	3.1	3.8	93
USF	0.6	0.5	0.4	0.8	0.4	0.7	49.4	20.9	1.8	13.3	0.3	0.4	0.5	0.3	0.4	0.4	0.3	51
UKF	1	0.8	0.5	0.9	0.7	1.2	17.7	39	2.7	17.7	0.5	0.6	0.6	0.6	0.5	0.6	0.5	61
JPF	0.8	0.8	0.8	1.1	1	1.2	9	9.3	42.7	6	1.2	1.1	1.1	0.9	1.1	0.8	1	57
GMF	0.4	0.4	0.1	0.6	0.3	0.7	15	22.3	1.8	49.2	0.2	0.3	0.4	0.2	0.3	0.3	0.2	51
HuaT	1.9	1.9	1.8	2.1	2.2	2.4	0.1	0.1	0.2	0	6.4	4.8	4.6	4.2	4.6	1.8	2.4	94
GFS	1.7	1.7	1.7	2	2	2.2	0.1	0.1	0.1	0.1	5	6.7	4.7	4.6	4.7	1.6	2.2	93
CMS	1.9	1.9	1.8	2.2	2.2	2.4	0.1	0.1	0.1	0.1	4.8	4.7	6.6	4.3	4.5	1.8	2.2	93
IS	1.7	1.6	1.6	2	2	2.2	0.1	0.2	0.1	0	4.7	4.9	4.6	7.1	4.7	1.5	2	93
ES	1.8	1.8	1.7	2.1	2.1	2.3	0.1	0.1	0.1	0.1	4.9	4.7	4.6	4.5	6.8	1.7	2.2	93
AB	3.7	5.3	3.4	3.4	4.8	3.5	0.1	0.2	0.1	0	2.2	1.9	2.1	1.7	1.9	7.7	4.6	92
EB	3.7	3.9	4	3.9	4.7	3.7	0.1	0.1	0.1	0	2.5	2.2	2.3	1.9	2.1	4	6.7	93
TO	89	88	81	95	99	100	46	59	11	39	107	103	104	96	101	88	102	**TC =**
NET	− 3	− 4	− 11	2	6	7	− 5	− 2	− 46	− 12	13	10	11	3	8	− 4	9	**88.6**

Notes: This table reports the full sample connectedness calculated from 10-step-ahead generalized VAR forecast error variance decomposition. TC, From, TO, and NET denote *total connectedness*, *total directional connectedness from others*, *total directional connectedness to others*, and *net total directional connectedness*, respectively. USF, UKF, JPF, and GMF represent the US financial market, UK financial market, Japanese financial market, and German financial market, respectively.

Appendix C

Table A-3
Total directional connectedness from each sector/market (%), 2011–2015.

	Total directional connectedness from								Nonbank	4GFM
	Trust	Securities	Insurance	Bank	USF	UKF	JPF	GMF		
SIT	10	49.3	8.8	31.8	0.1	0.2	0	0.1	68.1	0.4
SLS	3.2	61	8.2	27.5	0.1	0.2	0.1	0	72.4	0.4
GYS	3.1	58	8.8	29.7	0.1	0.1	0.1	0.1	69.9	0.4
HTS	2.5	53.8	9.2	34.2	0.1	0.1	0.1	0.1	65.5	0.4
PS	3.2	58.1	8	29.8	0.1	0.1	0.1	0	69.3	0.3
CJS	3	57.6	8	31.2	0.1	0.1	0.1	0	68.6	0.3
CS	2.6	53.2	9.4	34.4	0.1	0.1	0.1	0	65.2	0.3
NES	3.2	58.5	8.2	30	0.1	0.1	0.1	0	69.9	0.3
PAI	2	34.1	16.1	46.7	0.2	0.3	0.2	0.1	52.2	0.8
CLI	2	33.4	17.9	46	0.1	0.2	0.2	0.1	53.3	0.6
CPI	2.1	34.7	17.1	45.4	0.1	0.3	0.2	0.1	53.9	0.7
HXB	1.5	25.2	9	63.8	0.2	0.3	0.2	0.1	35.7	0.8
BOC	1	18.4	8.8	71.6	0	0.1	0.1	0	28.2	0.2
BON	1.8	28.8	8.7	60.2	0.1	0.2	0.1	0.1	39.3	0.5
CMB	1.2	24.2	9.7	64.1	0.2	0.3	0.2	0.1	35.1	0.8
IB	1.5	26.4	8.7	62.7	0.2	0.3	0.1	0.1	36.6	0.7
ICBC	1.1	20.2	8.5	69.7	0.1	0.2	0.2	0.1	29.8	0.6
BN	2	29.2	8.4	60	0.1	0.2	0.1	0.1	39.6	0.5
PAB	1.7	28.7	8.7	60.1	0.1	0.2	0.1	0.1	39.1	0.5
MSB	1.3	22	9.2	66.9	0.1	0.2	0.1	0.1	32.5	0.5
CCB	1.1	22.1	8.9	67.3	0.1	0.3	0.1	0.1	32.1	0.6
CB	1.2	23	8.5	66.8	0.1	0.2	0.1	0.1	32.7	0.5
BB	1.6	24.7	9.1	64	0.2	0.2	0.1	0.1	35.4	0.6
BC	1.3	23	9	66.1	0.1	0.2	0.2	0	33.3	0.5
PDB	1.4	26.4	8.6	62.6	0.2	0.3	0.2	0.1	36.4	0.8
USF	0.3	4.2	1.2	8.7	49.4	20.9	1.8	13.3	5.7	85.4
UKF	0.5	6.3	2.8	13.3	17.7	39	2.7	17.7	9.6	77.1
JPF	0.3	11.9	4.1	17	9	9.3	42.7	6	16.3	67
GMF	0.4	3.2	1.4	6.8	15	22.3	1.8	49.2	5	88.3
HuaT	2.7	53.1	8.7	34.9	0.1	0.1	0.2	0	64.5	0.4
GFS	2.9	55.9	8.8	32	0.1	0.1	0.1	0.1	67.6	0.4
CMS	2.7	53.4	8.6	35.1	0.1	0.1	0.1	0.1	64.7	0.4
IS	2.8	56.7	8.7	31.2	0.1	0.2	0.1	0	68.2	0.4
ES	2.8	55.3	8.3	33.3	0.1	0.1	0.1	0.1	66.4	0.4
AB	1.2	20.8	8.5	68.7	0.1	0.2	0.1	0	30.5	0.4
EB	1.3	23.5	9	66	0.1	0.1	0.1	0	33.8	0.3

Notes: This table reports the total directional connectedness of the 32 institutions in the Chinese financial sector (divided into Trust, Securities, Insurance, and Bank subsectors) or 4 global financial sectors (US, UK, Japan, and Germany). USF, UKF, JPF, and GMF represent the US financial market, UK financial market, Japanese financial market, and German financial market, respectively. Nonbanks: nonbank financial sector. 4GFM: four global financial sectors.

Appendix D

Table A-4
Full sample connectedness using financial institutions' filtered returns, 2008–2015.

	SIT	SLS	GYS	HTS	PS	CJS	CS	NES	PAI	CLI	CPI	HXB	BOC	BON	CMB	IB	ICBC	BN	PAB	MSB	CCB	CB	BB	BC	PDB	USF	UKF	JPF	GMF	FROM
SIT	54.8	3.7	7.5	4.8	6.4	6.4	3.8	6.4	0.2	0.2	0.3	0.3	0.7	0.1	0.5	0.3	0.6	0.5	0.2	0.2	0.6	0.2	0.1	0.4	0.5	0.1	0.1	0.3	0.1	45
SLS	2.5	36.5	11.2	8.6	9.5	9.5	7.6	10	0.3	0.6	0.3	0.2	0.2	0.1	0.2	0.2	0.3	0.2	0.1	0.2	0.2	0.1	0.1	0.4	0.2	0	0.3	0	0.4	63
GYS	4	9.1	29.8	10	9.6	12.3	8.4	12.1	0.6	0.8	0.9	0.1	0.1	0.2	0.1	0.1	0.1	0.4	0.2	0.1	0	0	0.1	0.2	0.2	0.1	0.2	0.1	0.1	70
HTS	2.5	6.8	9.9	29.9	7.8	11.9	13.8	8.9	1	1.5	1.7	0.4	0	0.3	0.2	0.5	0	0.4	0.5	0.2	0.1	0.2	0.3	0	0.5	0.2	0.2	0	0.2	70
PS	4	8.9	11.1	9.2	34.5	10.9	8.5	10	0.3	0.6	0.5	0	0.1	0.1	0	0.1	0.1	0.1	0.1	0	0	0	0	0.1	0.1	0.1	0.2	0	0.2	65
CJS	3.4	7.5	12.1	12	9.3	29.6	10.8	12.3	0.2	0.6	0.5	0	0.1	0.1	0.1	0.1	0.1	0.2	0.2	0	0	0	0.1	0	0.2	0	0.2	0	0.1	70
CS	2.1	6.1	8.5	14.3	7.5	11.1	30.6	8.5	1.5	2.5	1.8	0.5	0.1	0.3	0.3	0.8	0.2	0.4	0.8	0.1	0.2	0.4	0.1	0.1	1.2	0	0.1	0	0.1	69
NES	3.7	8.5	12.6	9.4	9.1	13.1	8.8	31.4	0.4	0.5	0.6	0	0.1	0	0.1	0	0.2	0.2	0.1	0	0.1	0	0	0.2	0.1	0.2	0.3	0.1	0.2	69
PAI	0	0.3	0.7	1.1	0.4	0.4	1.7	0.4	35.1	11.6	12.6	3.1	1.2	1.4	4.2	3.1	1.4	1	3.3	2.4	2.7	1.4	2.3	3.4	2.8	0.8	0.6	0.4	0.4	65
CLI	0.1	0.5	1	1.6	0.7	0.7	2.6	0.5	11.2	34.4	14	2.7	2	1.4	3.2	2.2	2.1	1.3	2	3.3	2.8	2.1	1.7	2.9	2.1	0.2	0.1	0.2	0.2	66
CPI	0.2	0.3	1	2.1	0.4	0.5	2.1	0.5	12.6	14.3	35	2.7	1.2	1.6	3.1	2.6	1.3	1.5	2.1	2.8	2.2	1.6	2.5	2.9	2	0.1	0.2	0.2	0.2	65
HXB	0	0	0	0.3	0	0	0.3	0	1.6	1.5	1.5	20.1	3.1	5.2	7.9	7.6	3.4	5.3	6.2	7.1	4.2	4.8	6.3	5.5	7.7	0.1	0.1	0	0.1	80
BOC	0.4	0.2	0.2	0.1	0.1	0.2	0	0.1	0.9	1.7	1	4.4	27.9	2.4	4.5	3.4	10	3.6	2.7	5.1	10.6	6.2	3.4	7.8	2.8	0	0	0	0	72
BON	0.1	0	0.2	0.2	0.1	0.1	0.2	0	0.9	1.1	1.1	6.5	2.1	24.6	5.4	6.9	3.3	10.1	5.1	5.1	3.2	4.2	8.4	4.8	6.1	0	0	0.1	0.1	75
CMB	0.1	0	0	0.2	0	0.1	0.2	0.1	2.3	1.9	1.7	8	3.2	4.4	20.3	7.8	4.2	3.9	5.7	6.9	4.5	4	5.8	6.1	7.9	0	0.1	0.2	0.1	80
IB	0	0	0	0.4	0	0	0.5	0	1.7	1.3	1.4	7.5	2.4	5.5	7.5	19.6	2.8	5.6	8.2	6.7	3.4	4.2	6.8	5	9.1	0	0.1	0.1	0.1	80
ICBC	0.3	0.2	0.1	0.1	0	0.1	0	0.2	1	1.7	1	4.7	9.8	3.7	5.8	4	27.5	2.6	2.9	5.1	10.7	4	3.4	7.5	3.4	0	0.1	0	0	73
BN	0.2	0	0.2	0.3	0.1	0.1	0.3	0.1	0.7	0.9	1	6.3	3.1	9.7	4.7	6.8	2.4	23.6	6	5.1	3.1	6.3	8	5.3	5.2	0.1	0.1	0	0.1	76
PAB	0	0	0.1	0.3	0	0.1	0.6	0.1	2.1	1.4	1.4	7.1	2.2	4.7	6.4	9.6	2.4	5.7	22.6	6.7	3.4	4.3	5.4	5	8.2	0	0.1	0.1	0.1	77
MSB	0	0	0	0.1	0	0	0.1	0	1.4	2	1.6	7.6	3.9	4.3	7.4	7.4	4	4.6	6.4	21.3	4.8	5.2	5.1	6.1	6.5	0	0.1	0	0.1	79
CCB	0.2	0.1	0	0.1	0	0	0.1	0	1.8	2.1	1.5	5.2	9.1	3.2	5.4	4.3	9.5	3.2	3.7	5.4	23.9	4.8	4.1	8	3.9	0.1	0.1	0.1	0	76
CB	0	0	0	0.2	0	0	0.3	0	1	1.7	1.2	6.1	5.7	4.3	5.1	5.5	3.8	6.8	4.9	6.2	5.2	25.7	5.7	6.4	3.9	0	0	0	0	74
BB	0	0	0	0.2	0	0	0.1	0	1.3	1.1	1.6	7	2.7	7.5	6.3	7.7	2.7	7.5	5.3	5.3	3.7	4.9	22.2	5.5	6.6	0	0	0	0.2	78
BC	0.1	0.2	0	0.1	0	0	0	0.1	2.1	2	1.8	5.9	5.8	4	6.5	5.5	5.9	4.6	4.7	5.9	7	5.3	5.3	21.1	5.4	0.1	0.2	0.1	0.1	79
PDB	0	0	0.1	0.4	0.1	0.1	0.8	0	1.7	1.3	1.2	8.1	2	5.3	8.2	9.8	2.5	4.7	7.7	6.3	3.2	3.2	6.4	5.3	21.2	0	0.2	0.1	0.1	79
USF	0.1	0	0.1	0.1	0	0	0	0.2	0.1	0.1	0.1	0	0.1	0	0.1	0	0	0	0	0	0.1	0.1	0.1	0.1	0	63.8	21	1	12.8	36
UKF	0.1	0.3	0.2	0.3	0.1	0.1	0.1	0.3	0.4	0.2	0.3	0.3	0.1	0	0.3	0.2	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.3	0.4	20.5	49.2	4	21.7	51
JPF	0.3	0	0.2	0	0	0	0	0.2	0.6	0.2	0.3	0.1	0.2	0.1	0.7	0.3	0.1	0	0.2	0	0.2	0.1	0.1	0.3	0.2	14.7	15.6	55.4	9.7	45
GMF	0	0.4	0.3	0.1	0.1	0.1	0	0.4	0.4	0.3	0.2	0.2	0.1	0.1	0.3	0.2	0.1	0	0.1	0.1	0	0	0.4	0.3	0.2	14.9	23.8	3.5	53.4	47
TO	24	53	77	76	61	78	72	71	51	56	53	95	61	70	95	97	64	75	80	87	76	68	82	90	87	52	64	11	47	**TC =**
NET	− 21	− 10	7	6	− 4	8	3	2	− 14	− 10	− 12	15	− 11	− 5	15	17	− 9	− 1	3	8	0	− 6	4	11	8	16	13	− 34	0	**68.1**

Notes: This table reports the full sample connectedness table calculated from 10-step-ahead generalized forecast error variance decomposition using the financial institutions' stock returns filtered by returns of Shanghai A-Share Stock Index.TC, From, TO, and NET denote *total connectedness*, *total directional connectedness from others*, *total directional connectedness to others*, and *net total directional connectedness*, respectively. USF, UKF, JPF, and GMF represent the US financial market, UK financial market, Japanese financial market, and German financial market, respectively.

References

Acemoglu, D., Carvalho, V.M., Ozdaglar, A., Tahbaz-Salehi, A., 2012. The network origins of aggregate fluctuations. Econometrica 80, 1977–2016.

Acemoglu, D., Ozdaglar, A., Tahbaz-Salehi, A., 2015. Systemic risk and stability in financial networks. Am. Econ. Rev. 105, 564–608.

Acharya, V., Engle, R., Richardson, M., 2012. Capital shortfall: a new approach to ranking and regulating systemic risks. Am. Econ. Rev. 102, 59–64.

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

Adrian, T., Brunnermeier, M.K., 2016. CoVaR. Am. Econ. Rev. 1705–1741.

Allahrakha, M., Glasserman, P., Young, H.P., 2015. Systemic importance indicators for 33 US Bank holding companies: an overview of recent data. Office of Financial Research Brief Series No. 15-01 1–7.

Allen, F., Qian, J., Qian, M., 2005. Law, finance, and economic growth in China. J. Financ. Econ. 77, 57–116.

Allen, F., Babus, A., Carletti, E., 2009. Financial Connections and Systemic Risk. Working Paper. University of Pennsylvania.

Allen, F., Qian, J., Zhang, C., Zhao, M., 2012. China's Financial System: Opportunities and Challenges. NBER Working Paper. (No. 17828).

Alpanda, S., Aysun, U., 2014. International transmission of financial shocks in an estimated DSGE model. J. Int. Money Financ. 47, 21–55.

Ayyagari, M., Demirgüç-Kunt, A., Maksimovic, V., 2010. Formal versus informal finance: evidence from China. Rev. Financ. Stud. 23, 3048–3097.

Bailey, W., Huang, W., Yang, Z., 2011. Bank loans with Chinese characteristics: some evidence on inside debt in a state-controlled banking system. J. Financ. Quant. Anal. 46, 1795–1830.

Ballester, L., Casu, B., González-Urteaga, A., 2016. Bank fragility and contagion: evidence from the bank CDS market. J. Empir. Financ. 38 (Part A), 394–416.

Benoit, S., Colletaz, G., Hurlin, C., Pérignon, C., 2013. A Theoretical and Empirical Comparison of Systemic Risk Measures. HEC Paris Research Paper No. FIN-2014-1030.

Benoit, S., Colliard, J.-E., Hurlin, C., Pérignon, C., 2017. Where the risks lie: a survey on systemic risk. Review of Finance 21, 109–152.

Berger, A.N., Hasan, I., Zhou, M., 2009. Bank ownership and efficiency in China: what will happen in the world's largest nation? J. Bank. Financ. 33, 113–130.

Bessler, D.A., Yang, J., 2003. The structure of interdependence in international stock markets. J. Int. Money Financ. 22, 261–287.

Brownlees, C., Engle, R.F., 2016. SRISK: a conditional capital shortfall measure of systemic risk. Rev. Financ. Stud. 30, 48–79.

Carpenter, J.N., Whitelaw, R.F., 2017. The development of China's stock market and stakes for the global economy. Annual Review of Financial Economics 9, 233–257.

Carpenter, J.N., Lu, F., Whitelaw, R.F., 2015. The Real Value of China's Stock Market. NBER Working Paper No. 20957.

Cetorelli, N., Goldberg, L.S., 2012. Banking globalization and monetary transmission. J. Financ. 67, 1811–1843.

Chen, X., Kim, K.A., Yao, T., Yu, T., 2010. On the predictability of Chinese stock returns. Pac. Basin Financ. J. 18, 403–425.

Collin-Dufresne, P., Goldstein, R.S., Martin, J.S., 2001. The determinants of credit spread changes. J. Financ. 56, 2177–2207.

Glasserman, P., Loudis, B., 2015. A Comparison of US and International Global Systemically Important Banks. Office of Financial Research Brief Series No. 15-07.

Hahm, J.-H., Mishkin, F.S., Shin, H.S., Shin, K., 2012. Macroprudential Policies in Open Emerging Economies. NBER Working Paper No. 17780.

Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions:0(,NEm m55.MisQerinkOGfxfl0fl,NtheOGfxflf,NEcon0x,Nde(r rhine5x(.,OGffj0(,NofOGffNi