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China's Financial Network with International Spillovers: A First Look

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Abstract

Using a modified spillover index approach from the perspective of financial shocks transmission, this study is the first to explore China's financial institution (FI) network after the global financial crisis, allowing for interactions with the financial sectors of four major global economies. We document that: (1) although banks still dominate China's financial sector, nonbank FIs also bear considerable influence; (2) the market-oriented large commercial banks generally play a more pronounced role than the four state-owned megabanks in transmitting financial shocks; (3) China's financial sector exerts noticeable influence on the global financial sector, particularly that of Japan; and (4) monetary policy measures dominate in determining the overall influence from other FIs to a particular FI while firm-specific factors dominate in determining the influence of a particular FI on other FIs. These findings have important policy implications.

Key Words

China's financial system
Systemic risk
Financial network
Shadow banking
Macroprudential regulation

JEL Classification

G01
G15

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清华大学国家金融研究院

初探中国金融网络的国际溢出效应

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【摘要】本文从金融冲击传导的角度刻画了国际金融危机后的中国金融机构网络，根据金融机构之间的相互影响以及单个金融机构对整体金融系统的净影响来识别系统重要性金融机构，并研究中国与四个主要国家金融体系之间的风险传染。本文得到以下结论：（1）尽管银行在中国的金融部门占主导地位，非银金融机构在金融风险传染中也起了重要作用，显示近年来中国影子银行问题的重要性。（2）以市场为导向的大型商业银行在金融风险传染过程中的影响比四大国有银行更为显著。（3）2008 年金融危机后，中国的金融机构的风险对四个

主要国家的金融机构的风险有显著的溢出效应，其中，对日本金融机构的影响尤为显著。（4）货币政策变化是影响其他金融机构对某一特定金融机构的溢出效应的主要因素，而各个金融机构的特质是决定该机构对整个系统风险溢出效应的主要因素。上述结论对中国的金融监管有重要的政策含义。

论文关键词

中国金融体系　　影子银行
系统性风险　　宏观审慎监管
金融系统

经济学文献分类号

G01
G15

INTRODUCTION

The 2015–2016 Chinese stock market turbulence triggered global fears over the possibility of another global crisis. [1] The worldwide anxiety again underscored the conventional wisdom prevailing since the 2008 global financial crisis: understanding the mechanism of financial shock transmission among financial institutions (FIs) is crucial to prevent the occurrence and propagation of financial crises, establish efficient regulation and supervision, and promote appropriate asset pricing and risk management (Acharya et al., 2012, 2017; Acemoglu et al., 2012, 2015; Adrian and Brunnermeier, 2016). Unfortunately, despite basic facts underscoring the global importance of China's financial system—China has the second-largest stock market in the world and the four biggest state owned Chinese banks (i.e., the Big Four—the Industrial and Commercial Bank of China, the Bank of China, the China Construction Bank, and the Agricultural Bank of China) are among the top ten FIs in the world—there is no comprehensive study on the financial shock transmission mechanism in China's financial system. This study attempts to fill this gap.

Based on a modified financial network analysis (Diebold and Yilmaz, 2014; Yang and Zhou, 2013), we investigate the network structure and potential determinants of financial shock transmission among China's FIs since the

[1] During the turbulence, the Shanghai stock market had fallen 30% within a month (by July 9, 2015), and eventually lost 50% until the market became tranquil in February 2016. China's stock market slump in 2015 dominated discussions at the October 2015 International Monetary Fund (IMF) annual meeting of global finance ministers and central bankers held in Peru, with participants asking whether "China's economic downturn [would] trigger a new financial crisis." Interestingly, Allen et al. (2012) also suggested that China should be vigilant against a "twin crisis" consisting of simultaneous foreign exchange and banking/stock market crises, which would impair sustainable economic growth in China.

onset of the 2008 global financial crisis, while controlling for the interactions between China and the four countries with the largest global financial services sectors (i.e., the United States [US], the United Kingdom [UK], Germany, and Japan). Similar to Diebold and Yilmaz, 2014 and Yang and 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

[2] As discussed in more detail later in the literature review, recent studies such as Carpenter et al. (2015) suggest good informational quality of stock prices of Chinese listed companies.
[3] These are the Marginal Expected Shortfall and the Systemic Expected Shortfall of Acharya et al. (2012), the Systemic Risk Measure of Acharya et al. (2017) and Brownlees and Engle (2016), and the Delta Conditional Value-at-Risks of Adrian and Brunnermeier (2016).

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 autoregression (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.

We also present new evidence that after the global financial crisis, China's financial sector has surprisingly exerted considerable influence on the financial sectors in the four major developed countries. This influence is especially evident in the Japanese financial sector. Such a finding is intriguing, given the well-documented low correlations between Chinese and major global stock markets, especially between China and Japan (Carpenter et al., 2015; Jach, 2017), and the fact that China's financial system is "centrally controlled, bank-dominated, uniquely relationship-driven, […], rather than based primarily on securities markets and legal contracts" (Carpenter and Whitelaw, 2017).[4]

Second, we contribute to the growing literature on systemic risk by exploring the transmission network among China's FIs while controlling for the influence from the financial sectors of major economies. Despite the fact that since 2008, four of the ten largest FIs in the world are Chinese, we are the first (to our best knowledge) to attempt a comprehensive examination of the pattern and determinants of financial shock transmission in China. Acemoglu et al. (2015, p. 564) argue that "the exact role played by the financial system's architecture in creating systemic risk remains, at best, imperfectly understood." The argument is even stronger in the case of China, given the unique features of its financial system,[5] as pointed out in Carpenter and Whitelaw (2017).

[4] The above features could imply that China's financial sector might be informationally lagging or even still largely segmented from the rest of the world. The existing literature also documents macroeconomic spillover only from the US to China (e.g., Pang and Siklos, 2016) but little from China to the US. However, as correctly pointed out by Carpenter and Whitelaw (2017), we should avoid over-applying research findings developed for the US setting to understand China's distinctive financial system.

[5] Take Chinese stock markets as an example. Such special features include 1-day minimum holding period, a 10% daily price move limit, short-sale restriction, trading suspension, IPO suspension, direct government intervention, and special treatment status for distressed stocks, as well as nontradable shares, market segmentation, and limited institutional participation (Carpenter and

We document a striking new finding that the market-oriented large commercial banks often play a more pronounced role than the Big Four in the financial shock transmission network, despite the latter's predominance in China's banking system. However, the role of these FIs is not static but changes quite dramatically over time. Interestingly, the Big Four do become relatively more influential in terms of financial shock transmission, primarily during turbulent periods (the 2008 financial crisis and the 2015 Chinese stock market crash), compared to tranquil periods. Further, extending many earlier studies (e.g., Yang and Zhou, 2013; Ballester et al., 2016; Helwege and Zhang, 2015), we find that various macroeconomic factors, especially China's monetary policy measures (including the money supply, interbank lending rate, and exchange rate), dominate in determining the influence of others on a particular FI in China. Meanwhile, we also find that firm-specific factors (e.g., leverage, size, and so on) dominate in determining the influence of an FI on other entities (as well as the net influence) in the network of financial shock transmission. These findings are supportive of the argument that microprudential regulation and supervision based on the conventional firm-specific approach are particularly insufficient to ensure financial stability in emerging economies, as underscored by Hahm et al. (2012). 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.

Whitelaw, 2017). All these unique features point to the real possibility that the findings on the US and other developed countries might or might not apply in China's setting.

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).

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 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

[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.

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.

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.

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

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

a similar composite 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.

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 datagenerating process of the stock returns of Chinese FIs and the financial sectors of the four major foreign

[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.

countries (i.e., the US, the UK, Germany, and Japan) follow an N-dimensional covariance-stationary VAR system:

$$X_t = \sum_{i=1}^{P} \Phi_i X_{t-i} + \alpha + \varepsilon_t \tag{1}$$

where X is a vector of the stock (or financial market) returns, α is the deterministic component of the VAR system, and ε~(0,Σ) is a vector of independently and identically distributed disturbances.

The moving average representation of Eq. (1) can then be written as $X = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$, where A_i is the N×N coefficient matrix obeying the recursive rule of $A_i = \Phi_1 A_{t-1} + \Phi_2 A_{t-2} + \cdots + \Phi_P A_{t-P}$, and A0 is an N×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 $X_i (i \neq j)$ invariant to the order of the variables. [9]

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

[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.

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

where Σ is the variance matrix, ε, σ_{jj} is the standard deviation of the error term for the j-th equation and e_j 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:

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

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 dij 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:

$$C_{i\leftarrow j}^{H} = d_{ij}^{H} \tag{4}$$

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:

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

Table 2 Connectedness Table Schematic

	x_1	x_2	$\cdots$	x_N	From others
x_1	${d_{11}}^H$	${d_{12}}^H$	$\cdots$	${d_{1N}}^H$	$\Sigma_{j=1}{}^N {d_{1j}}^H,\ j \neq 1$
x_2	${d_{21}}^H$	${d_{22}}^H$	$\cdots$	${d_{2N}}^H$	$\Sigma_{j=1}{}^N {d_{2j}}^H,\ j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	${d_{N1}}^H$	${d_{N2}}^H$	$\cdots$	${d_{NN}}^H$	$\Sigma_{j=1}{}^N {d_{Nj}}^H,\ j \neq N$
To others	$\Sigma_{i=1}{}^N {d_{i1}}^H,\ i \neq 1$	$\Sigma_{i=1}{}^N {d_{i2}}^H,\ i \neq 2$	$\cdots$	$\Sigma_{i=1}{}^N {d_{iN}}^H,\ i \neq N$	$\frac{1}{N}\sum_{i,j=1}^N d_{ij}^H,\ i \neq j$

Source: Diebold and Yilmaz (2014).

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

$$C_{i \leftarrow j}^H = \sum_{j=1, i \neq j}^N \tilde{d}_{ij}^H \tag{6}$$

The total directional connectedness to others from i is:

$$C_{j \leftarrow i}^H = \sum_{i=1, i \neq j}^N \tilde{d}_{ij}^H \tag{7}$$

Then, the net total directional connectedness is:

$$C_{j \leftarrow i}^H = \sum_{i=1, i \neq j}^N \tilde{d}_{ij}^H \tag{8}$$

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.

FULL SAMPLE RESULTS AND ROBUSTNESS CHECKS

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 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

[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).

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.

Table 3 Full Sample Connectedness of 25 Financial Institutions and 4 Major Global Financial Sectors, 2008-2015

[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.

	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
BOC	1.9	1.7	2.1	2.4	2.1	2.3	2.6	2.2	3.5	3.8	3.6	4.6	9.3	4	4.7	4.4	5.8	4.6	4.1	4.7	6.1	5	4.3	5.5	4	0.1	0.2	0.3	0.1	91
BON	2.5	2.2	2.8	2.8	2.6	2.8	3	2.6	3.4	3.5	3.6	4.9	3.5	8	4.7	5	3.8	5.8	4.6	4.4	4	4.2	5.3	4.5	4.7	0.1	0.2	0.3	0.1	92
CMB	2	1.8	2.2	2.6	2.2	2.4	2.9	2.2	3.9	3.7	3.8	5.4	3.9	4.5	7.8	5.3	4.1	4.5	4.8	5	4.4	4.2	4.8	4.9	5.2	0.2	0.3	0.4	0.3	92
IB	2.3	1.9	2.4	2.8	2.2	2.6	3.1	2.4	3.6	3.5	3.6	5.2	3.6	4.7	5.2	7.6	3.7	4.9	5.4	4.9	4.1	4.2	5	4.6	5.5	0.1	0.3	0.3	0.2	92
ICBC	2	1.6	2.1	2.4	2.1	2.3	2.6	2.1	3.4	3.8	3.6	4.7	5.8	4.4	4.9	4.5	9.3	4.2	4.1	4.7	6.1	4.3	4.3	5.5	4.1	0.2	0.3	0.3	0.2	91
BN	2.7	2.3	2.8	2.9	2.6	3	3.2	2.8	3.3	3.4	3.6	4.8	3.8	5.5	4.5	5	3.5	7.7	4.8	4.4	4	4.7	5.2	4.6	4.5	0.1	0.2	0.2	0.1	92
PAB	2.5	2	2.5	2.8	2.3	2.7	3.2	2.6	3.8	3.5	3.6	5.1	3.5	4.5	4.9	5.6	3.5	4.9	7.9	4.9	4.1	4.2	4.7	4.6	5.2	0.1	0.2	0.3	0.1	92
MSB	2.2	1.7	2.2	2.6	2.1	2.4	2.7	2.2	3.5	3.8	3.7	5.3	4.1	4.5	5.3	5.3	4.1	4.7	5	8.1	4.5	4.6	4.7	5	4.9	0.1	0.3	0.2	0.2	92
CCB	2	1.7	2.3	2.6	2.3	2.4	2.8	2.2	3.8	3.9	3.8	4.7	5.5	4.2	4.8	4.5	5.5	4.3	4.3	4.7	8.3	4.5	4.4	5.4	4.2	0.2	0.3	0.3	0.2	92
CB	2.2	1.9	2.3	2.7	2.3	2.5	3	2.3	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	8.6	4.8	5	4.2	0.1	0.2	0.3	0.2	91
BB	2.3	1.8	2.3	2.8	2.2	2.6	2.9	2.3	3.6	3.5	3.8	5.1	3.7	5.3	5	5.3	3.7	5.4	4.7	4.6	4.3	4.5	8	4.8	4.9	0.1	0.2	0.3	0.2	92
BC	2.1	1.6	2.2	2.5	2.1	2.4	2.7	2.1	3.8	3.8	3.8	4.9	4.7	4.4	5	4.8	4.6	4.7	4.6	4.8	5.1	4.6	4.7	7.9	4.6	0.3	0.4	0.4	0.3	92
PDB	2.2	1.9	2.4	2.8	2.3	2.7	3.3	2.4	3.6	3.4	3.5	5.4	3.4	4.7	5.4	5.8	3.5	4.7	5.3	4.9	4	3.9	4.9	4.7	8	0.1	0.3	0.3	0.2	92
USF	0	0	0	0	0	0	0.1	0.1	0.2	0.2	0.2	0.1	0.1	0.1	0.2	0.1	0.1	0.1	0.1	0.1	0.2	0.1	0.1	0.2	0.1	63.1	20.8	1	12.6	37
UKF	0.3	0.1	0.2	0.4	0.3	0.3	0.4	0.3	1.3	1	1.1	0.9	0.6	0.5	1.1	0.9	0.8	0.7	0.9	0.9	0.8	0.5	0.7	1	1.2	17.8	42.7	3.4	18.8	57
JPF	0.5	0.7	0.6	1	0.9	0.9	1.3	0.7	2.2	1.7	1.8	1.3	1.2	1.5	2.2	1.5	1.3	1.2	1.5	1.2	1.6	1.2	1.3	1.8	1.6	10.4	11	39	6.8	61
GMF	0.3	0.1	0.3	0.3	0.2	0.3	0.4	0.3	1.1	1.1	0.9	0.8	0.5	0.5	1	0.8	0.7	0.6	0.7	0.7	0.5	0.4	0.9	0.9	1	13.2	21.1	3.1	47.2	53
TO	71	70	86	91	82	90	97	85	94	97	97	104	84	99	103	106	84	105	101	97	95	91	99	101	100	45	59	15	43	TC=
NET	−18	−19	−5	0	−8	−1	5	−6	3	5	5	12	−7	7	11	14	−7	13	9	5	3	0	7	9	8	8	2	−46	−10	85.9

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 in the table represent the US financial market, UK financial market, Japan financial market, and German financial market, respectively.

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 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.

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.

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

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

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.

Table 5 Robustness Checks

	Basic Results			Banking Index			Nonsynchronous			32 Institutions			Filtered returns		
	From	To	Net	From	To	Net	From	To	Net	From	To	Net	From	To	Net
SIT	89	71	−18	89	71	−18	89	74	−15	90	65	−25	45	24	−21
SLS	89	70	−19	89	70	−19	89	71	−18	91	70	−21	63	53	−10
GYS	91	86	−5	91	86	−5	91	88	−3	92	90	−2	70	77	7
HTS	91	91	0	91	91	0	91	91	0	93	103	10	70	76	6
PS	90	82	−8	90	82	−8	90	83	−7	92	86	−6	65	61	−4
CJS	91	90	−1	91	90	−1	91	92	1	93	95	2	70	78	8
CS	92	97	5	92	97	5	92	99	7	94	106	12	69	72	3
NES	91	85	−6	90	85	−5	91	86	−5	93	92	−1	69	71	2
PAI	91	94	3	91	94	3	92	102	10	93	103	10	65	51	−14
CLI	92	97	5	92	97	5	92	101	9	93	91	−2	66	56	−10
CPI	92	97	5	92	97	5	92	101	9	93	99	6	65	53	−12
HXB	92	104	12	92	104	12	92	105	13	94	109	15	80	95	15
BOC	91	84	−7	91	84	−7	91	86	−5	91	76	−15	72	61	−11
BON	92	99	7	92	99	7	92	101	9	93	101	8	75	70	−5
CMB	92	103	11	92	103	11	92	107	15	93	99	6	80	95	15
IB	92	106	14	92	106	14	93	108	15	94	108	14	80	97	17
ICBC	91	84	−7	91	84	−7	91	87	−4	91	79	−12	73	64	−9
BN	92	105	13	92	105	13	92	106	14	94	106	12	76	75	−1
PAB	92	101	9	92	101	9	92	103	11	93	102	9	77	80	3
MSB	92	97	5	92	97	5	92	100	8	92	89	−3	79	87	8
CCB	92	95	3	92	95	3	92	99	7	92	88	−4	76	76	0
CB	91	91	0	91	91	0	92	94	2	92	81	−11	74	68	−6
BB	92	99	7	92	99	7	92	101	9	93	95	2	78	82	4
BC	92	101	9	92	101	9	92	106	14	93	99	6	79	90	11
PDB	92	100	8	92	100	8	92	103	11	93	100	7	79	87	8
USF	37	45	8	37	42	5	52	35	−17	51	46	−5	36	52	16
UKF	57	59	2	52	51	−1	68	40	−28	61	59	−2	51	64	13
JPF	61	15	−46	53	13	−40	63	37	−26	57	11	−46	45	11	−34
GMF	53	43	−10	49	40	−9	63	27	−36	51	39	−12	47	47	0
HuaT										94	107	13			
GFS										93	103	10			
CMS										93	104	11			
IS										93	96	3			
ES										93	101	8			
AB										92	88	−4			
EB										93	102	9			
TC	85.9			85.3			87.3			88.6			68.1		

Notes: This table reports the total directional connectedness from other institutions (From), to others (To), and net total directional connectedness (Net) of each financial institution in the risk transmission network obtained from four robust checks: 1) using the bank index rather than the financial sector index to control for the influence from four global financial sectors (Banking Index); 2) modeling the US, UK, and German financial sectors as the leading markets (Nonsynchronous); 3) incorporating more financial institutions (32 institutions); and 4) using the financial institutions' stock returns filtered by the returns of Shanghai A-Share Stock Index (Filtered returns). The results estimated previously (Basic Results) are also presented to facilitate comparison. TC: total connectedness.

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. 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 the FIs' stock returns by regressing each return series on the return of the Shanghai A-Share Stock Index and then recast our analysis using the filtered returns.

Table 5 reports the total directional connectedness from others, to others, and the net total directional connectedness of each FI (or sector) extracted from the four robustness checks, along with the results estimated previously to facilitate comparison. Clearly, the main results remain almost the same for the 25 FIs using banking indices. The results of modeling the US, UK, and German financial sectors as the leading markets also yield very similar inferences to what we obtained based on matching the same calendar day. However, these results do show somewhat higher total directional connectedness from others, lower total directional connectedness 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 development of China's financial market

[14] See Appendix Table A-1 for the full sample connectedness table of modeling the US, UK, and German financial sectors as the leading markets in the alternative definition of a trading day.

and call for a more in-depth investigation of the dynamic transmission network of financial shocks below.

The result driven from using FIs' filtered returns shows a mitigated and yet still highly interconnected pattern of Chinese FIs, without changing our main findings. In particular, banks still dominate China's financial sector, and nonbank FIs also bear considerable influence. The market-oriented large commercial banks also still generally play a more pronounced role than the Big Four in transmitting financial shocks. Finally, although the connectedness apparently decrease as we filter out common components of FIs' returns, the results still show positive net pairwise directional connectedness from China's financial sector to the UK, Japan, and German financial sectors.[15] Thus, the basic results above largely reflect true interconnectedness rather than being mainly driven by common components. In summary, the main results generally remain robust.

DYNAMIC CONNECTEDNESS AND ITS DETERMINANTS

In what follows, we attempt to answer two important questions arising from our previous analysis: 1) Is the transmission of financial shocks among China's FIs variable over time? 2) If so, what major factors contribute to this variation?

Dynamic Connectedness

The full sample result is informative about what occurred on average during the full sample period. However, it is less helpful to ensure effective financial

[15] See Appendix Table A-4 for the full sample connectedness table of using the filtered returns.

regulation and supervision, which requires up-to-date information about the dynamic transmission of financial shocks as well as the potential role each FI plays in the network. To this end, similar to Diebold and Yilmaz, 2014, we use a 120-trading-day (one-half year)[16] fixed rolling window to extract the dynamic connectedness of each FI (or market). Figs. 1, 2, and 3 depict the extracted net total directional connectedness, the total directional connectedness from others, and the total directional connectedness to others for each FI (or market), respectively. These dynamic connectedness patterns re-confirm our previous full sample conclusions while also having several implications for financial regulation and supervision. First, both the total directional connectedness from others (Fig. 2) and the total directional connectedness to others (Fig. 3) change over time, which results in timevarying net total directional connectedness (Fig. 1). These findings imply that the role each institution plays in financial shock transmission also changes over time. The conventional approach of identifying SIFIs based on low-frequency financial indices (e.g., IMF, BIS, and FSB, 2009; Allahrakha et al., 2015; Glasserman and Loudis, 2015) may fail to capture these dynamic changes. Thus, these indices are hardly able to serve the full purpose of efficient regulation and supervision.

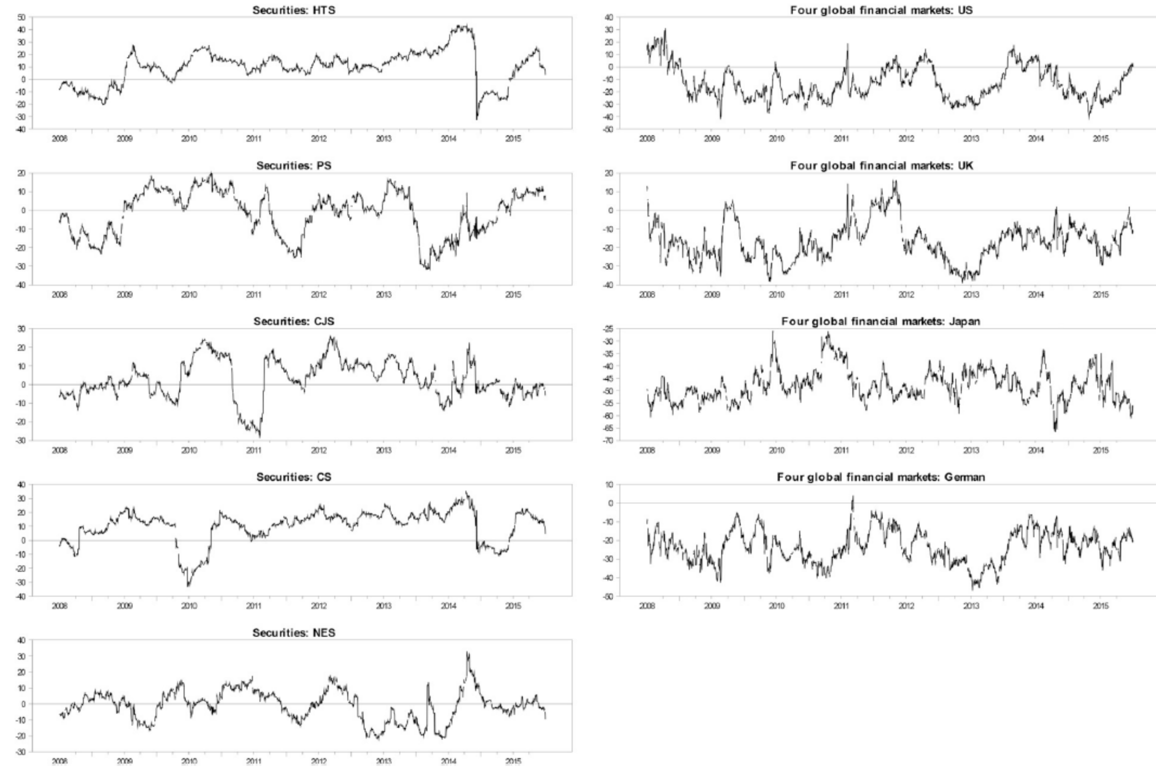
Second, the dynamic financial shock transmission patterns confirm the dominant role of banks in China's financial system as well as the growing importance of nonbanking FIs. Consistent with the full sample result, the dynamic net total directional connectedness of banks exhibits a higher frequency of positive net influence in the financial shock transmission

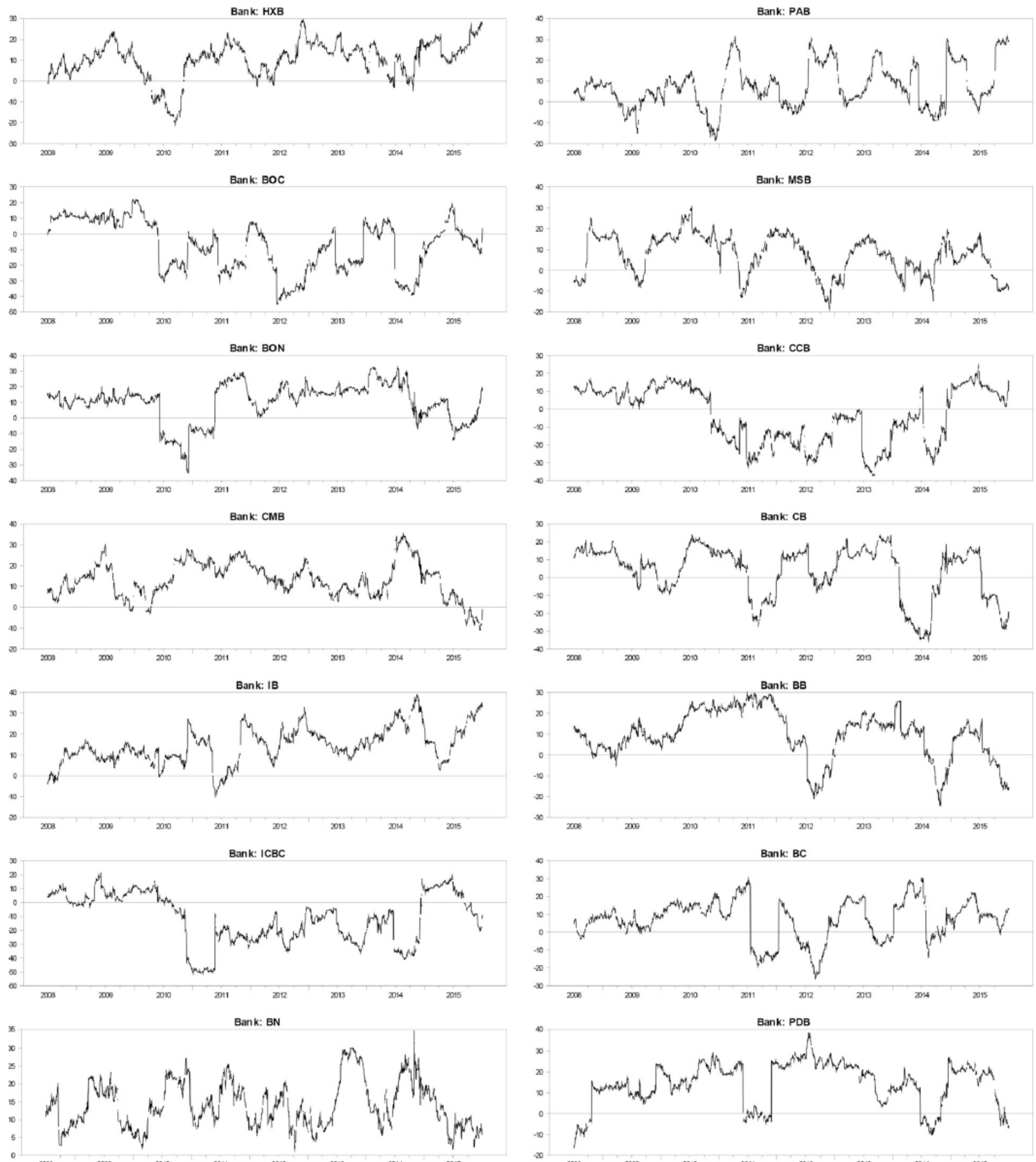
[16] In China, trading days of the stock market are roughly 240 days per year, due to additional public holidays such as the 1-week Spring Festival, and so on.

network (Fig. 1-Panel B) than the nonbank FIs (Fig. 1-Panel A). However, the 11 nonbank FIs (especially the three insurance sector FIs and a few institutions in the securities sector) each exert a positive net influence in the financial shock transmission network during most of the sample period.

Third, the market-oriented commercial banks have much greater influence than the Big Four in the financial shock transmission network. The SIFIs identified from the previous full sample connectedness table, that is, Huaxia Bank (HXB), China Merchants Bank (CMB), and Industrial Bank (IB) among others, exert a positive net influence more frequently in the financial shock transmission network. Nevertheless, an interesting result of the three incorporated Big Four banks is that they exert a positive net influence during the turmoil period (2008 financial crisis and the 2015 Chinese stock market crash) but a negative net influence during other tranquil periods in the financial shock transmission network.

Figure 1 Dynamic Net Total Directional Connectedness, 2008-2015.
A: 11 Nonbank Financial Institutions and 4 Global Financial Sectors
B: 14 Banks


Securities: HTS
Four global financial markets: US
Securities: PS
Four global financial markets: UK
Securities: CJS
Four global financial markets: Japan
Securities: CS
Four global financial markets: German
Securities: NES



Determinants of Dynamic Connectedness

We have investigated the full sample and the dynamic transmission of financial shocks among China's FIs. A natural question is then, what are the major factors that produced such a network? To answer this question, we follow Yang and Zhou (2013) and 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 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.

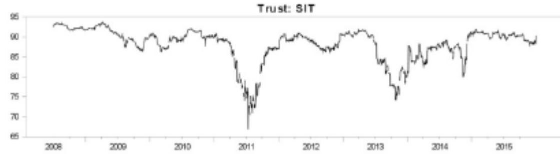
Macroeconomic Factors

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 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 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.

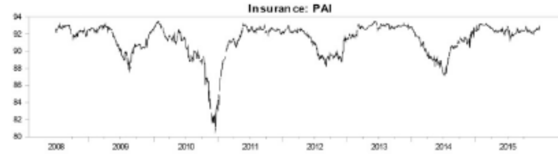
Figure 2 Dynamic Total Directional Connectedness from Others, 2008-2015.
A:11 Nonbank Financial Institutions and 4 Global Financial Sectors
B: 14 Banks

[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-R2 equal to or>1%) as meeting the minimum threshold of economic significance.

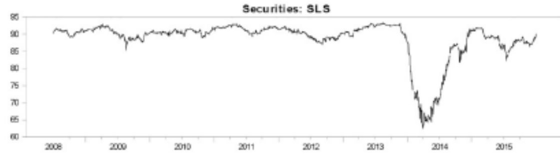
Trust: SIT



Insurance: PAI

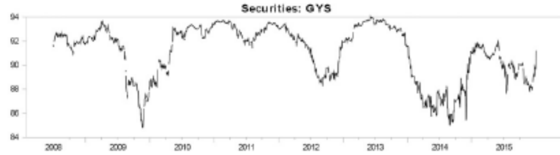


Securities: SLS

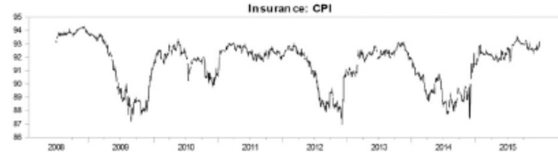


Insurance: CLI

Securities: GYS



Insurance: CPI



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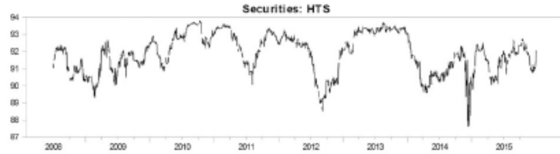
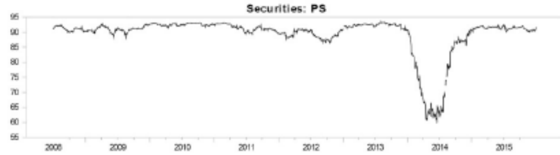


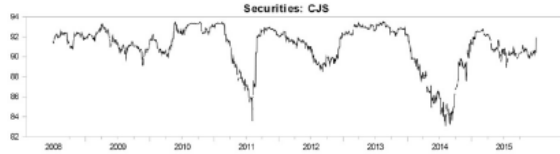
Four global financial markets: US

Securities: PS



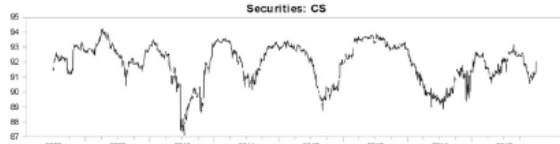
Four global financial markets: UK

Securities: CJS



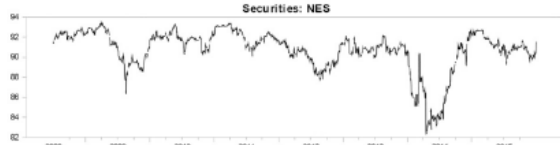
Four global financial markets: Japan

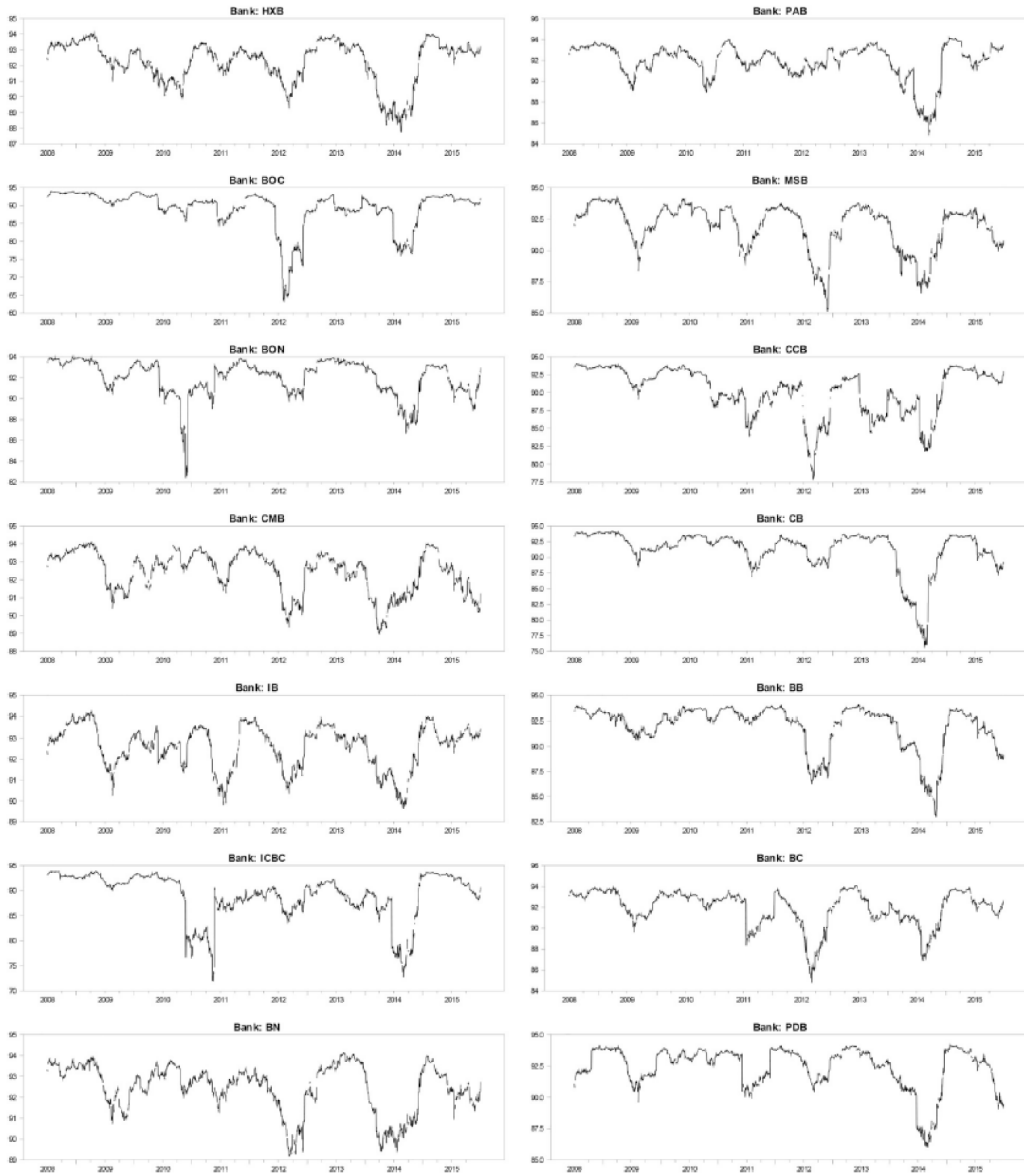
Securities: CS



Four global financial markets: German

Securities: NES

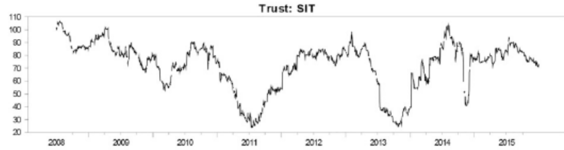




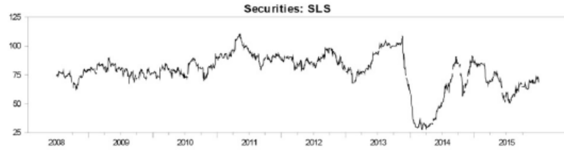
First, we examine whether the transmission of financial shocks is affected by various monetary policy measures. An important monetary measure in China is the money supply, particularly M2 and its various components (quasi money and its three components, i.e., saving deposits, time deposits, and other 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' component.

Figure 3 Dynamic Total Directional Connectedness to Others, 2008-2015.
A:11 Nonbank Financial Institutions and 4 Global Financial Sectors
B: 14 Banks

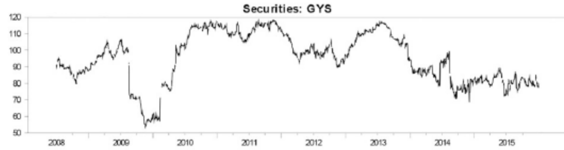
Trust: SIT



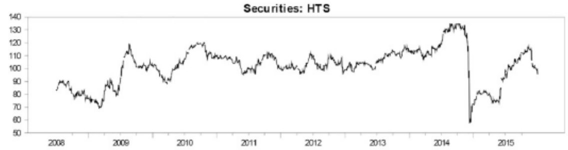
Securities: SLS



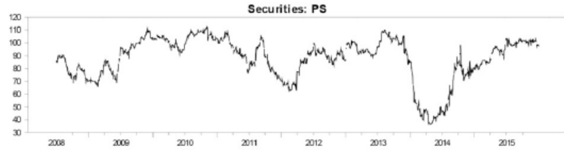
Securities: GYS



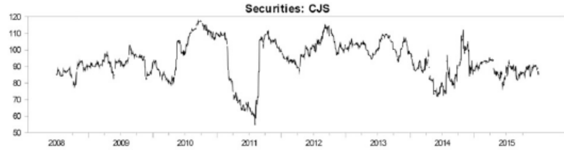
Securities: HTS



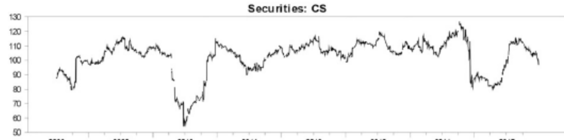
Securities: PS



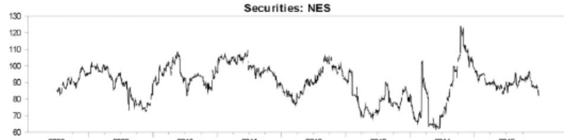
Securities: CJS



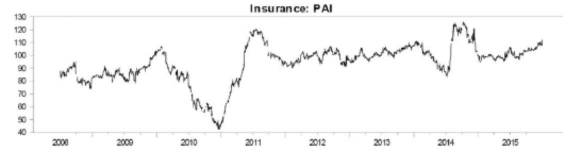
Securities: CS



Securities: NES

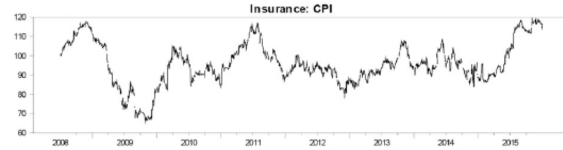


Insurance: PAI

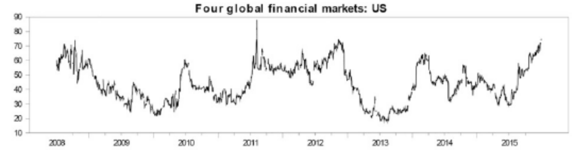


Insurance: CLI

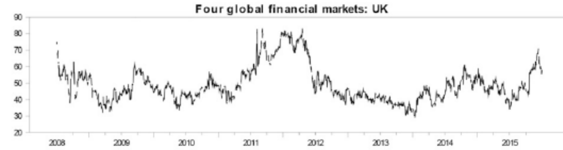
Insurance: CPI



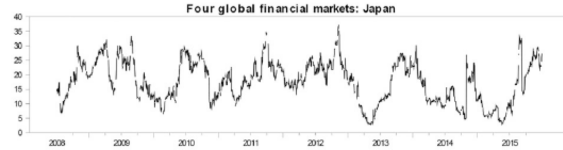
Four global financial markets: US



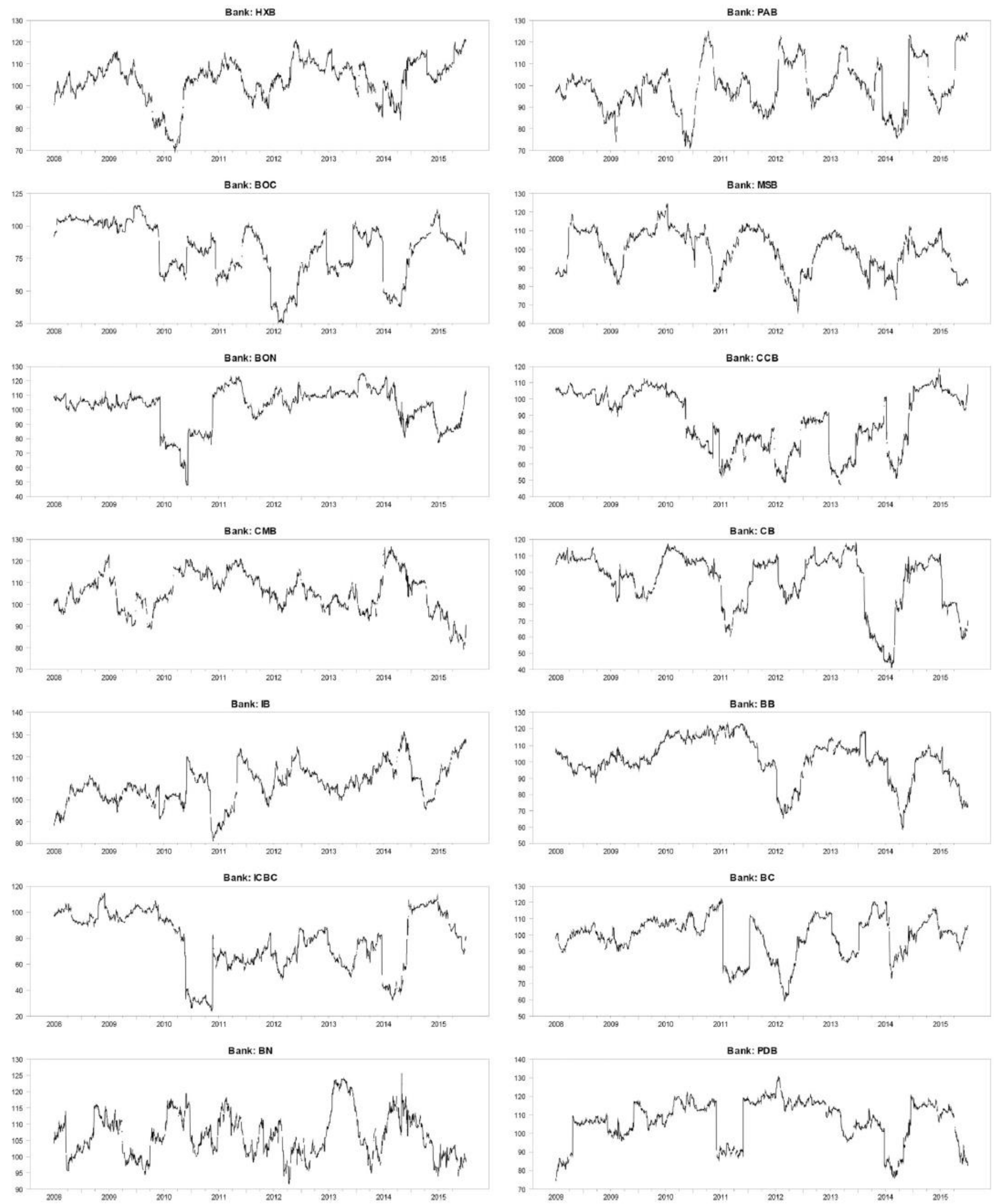
Four global financial markets: UK



Four global financial markets: Japan

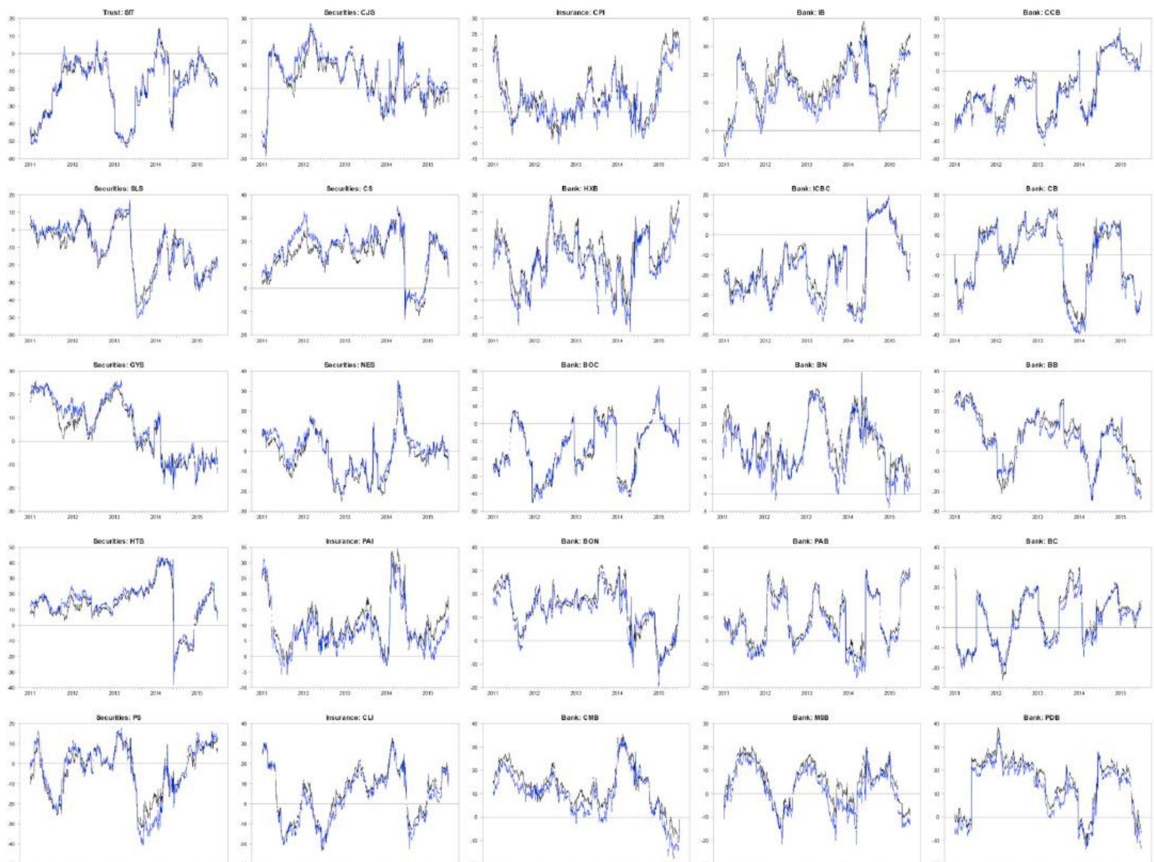


Four global financial markets: German



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 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.

Figure 4 Net Total Directional Connectedness of 25 Financial Institutions Extracted from 2008 to 2015 and 2008-2015 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.

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).

[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.

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

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*****	**1728**	**0.029**	−1.543	1728	0.002
	(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	**−0.522*****	**992**	**0.023**	−0.855	992	0.001
	(1.089)			(0.183)			(1.238)		
Wenzhou private lending rate: average (%)	−0.215	1376	−0.000	**−0.256*****	**1376**	**0.020**	−0.471	1376	0.001
	(0.443)			(0.054)			(0.489)		
Wenzhou private lending rate: automobile mortgage (%)	−0.137	1376	−0.001	**−0.394****	**1376**	**0.018**	−0.531	1376	0.000
	(0.882)			(0.154)			(1.005)		
Wenzhou private lending rate: real estate mortgage (%)	−0.185	1376	−0.000	−0.095*	1376	0.001	−0.281	1376	−0.000
	(0.419)			(0.051)			(0.460)		
Insurance sector: bank deposit, RMB bn (log-)	3.366	1728	0.000	−0.502	1728	0.000	2.864	1728	−0.000
	(5.650)			(0.772)			(6.257)		
Insurance sector: portfolio investment, RMB bn (log-)	1.395	1728	−0.000	0.361	1728	0.001	1.756	1728	0.000
	(2.736)			(0.364)			(3.010)		
Panel D: Exchange rate and currency swaps									
Real efficient exchange rate (2010 = 100)	0.047	1728	0.000	**0.048*****	**1728**	**0.024**	0.095	1728	0.002
	(0.079)			(0.009)			(0.086)		
Currency swap: 1 week (%)	−0.000	1728	−0.001	−0.001**	1728	0.000	−0.001	1728	−0.001
	(0.003)			(0.000)			(0.003)		
Currency swap: 1 month (%)	−0.000	1728	−0.001	0.002***	1728	0.002	0.002	1728	−0.001
	(0.009)			(0.001)			(0.010)		
Currency swap: 3 month (%)	−0.025	1728	−0.000	−0.018***	1728	0.004	−0.043	1728	0.000
	(0.035)			(0.006)			(0.040)		
Currency swap: 6 month (%)	−0.012	1728	−0.000	−0.014***	1728	0.007	−0.027	1728	0.000
	(0.029)			(0.005)			(0.033)		
Currency swap: 9 month (%)	−0.027	1728	−0.000	−0.028***	1728	0.009	−0.055	1728	0.000
	(0.055)			(0.010)			(0.063)		
Currency swap: 1 year (%)	−0.017	1728	−0.000	−0.019**	1728	0.005	−0.035	1728	−0.000
	(0.041)			(0.007)			(0.047)		
Panel E: Banking Climate Indices (BCI, %)									
BCI: degree of economy was overheated	−0.025	1728	−0.000	0.012	1728	0.002	−0.012	1728	−0.001
	(0.068)			(0.009)			(0.075)		
BCI: industry climate	−0.046	1728	−0.001	−0.011	1728	0.000	−0.057	1728	−0.000
	(0.095)			(0.011)			(0.103)		

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)		

7-B: Multiple regressions

	Dependent variables		
	(1)	(2)	(3)
	Net	From	To
Money supply, M2, Quasi money: other deposit, YoY-growth	−0.020	−0.060***	−0.080
	(0.062)	(0.013)	(0.073)
SHIBOR 1 year	−0.137	−0.761***	−0.898
	(2.078)	(0.243)	(2.296)
Yu'e Bao 7-day anualized return	−0.386	0.028	−0.358
	(1.929)	(0.360)	(2.229)
Wenzhou private lending rate: automobile mortgage	0.176	0.092	0.269
	(0.863)	(0.163)	(0.987)
Real efficient exchange rate	−0.026	0.189***	0.163
	(0.193)	(0.036)	(0.222)
Banking climate indices: money policy sentiment	0.022	−0.032	−0.011
	(0.144)	(0.020)	(0.161)
Constant	6.701	75.508***	82.209***
	(25.835)	(4.157)	(29.175)
Observations	992	992	992
Adj-R^2	−0.005	0.239	0.003

Notes: This table reports 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.

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.

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 affecting credit risk spillovers among American and European banks around the time of the recent global financial crisis. We find that the long-term debt to total assets ratio positively influences the total directional connectedness from others, to others, and the net total directional connectedness, while the short-term debt to total assets ratio negatively influences these types of connectedness. The net result is that the total debt to total assets ratios loses statistical significance. [20]

Second, we examine whether the transmission of financial shocks is affected by FIs' (short-term) liquidity, as measured by the accounts receivable turnover, the ratio of liquid assets to total assets, the ratio of current assets to total assets, and receivables to total asset. Accounts receivable turnover is an important proxy for short-term liquidity, and has a negative influence, which decreases the influence of an FI in the shock transmission networks. Similarly, we find that the ratio of liquid assets negatively affects the influence of an FI in the financial shock transmission network (net, from, and to), while the current assets ratio and receivable assets generally have no statistical significance. These findings are also generally consistent with the above negative influence of short-term debt to total assets.

[20] According to the definitions, total debt to total asset=long-term debt to total asset + short-term debt to total asset.

Third, we consider the influence of FI size. Largely consistent with the insignificant results of Yang and Zhou (2013) concerning the largest American and European FIs, we find the size may even have a negative impact on the transmission of financial shocks among Chinese FIs. This finding may add another caveat on the conventional argument of "too big to fail," with additional evidence from China. Nevertheless, as most of the FIs studied are among the largest in China, as noted by Yang and Zhou (2013), the result does not necessarily mean that their size does not affect the roles of risk transfer. Rather, the result only implies that among the largest FIs, the relative size may not be related to the relative influence within the financial shock transmission network. On the contrary, there is an alternative explanation. Size is one of the key factors suggested by the Basel Committee for the identification of 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.

[21] The intangible assets to total assets ratio is excluded because of its perfect collinearity with tangible assets to total assets.

In particular, the estimated coefficients lose their statistical significance and the adjusted R2 turns out to be comparatively lower (Columns 1–3 of Table 8-B). Then, we conduct another set of multiple regressions while excluding accounts receivable turnover (Columns 4–6 of Table 8-B), and find that:1) The four variables that significantly affect total directional connectedness from others, to others, and the net total directional connectedness are short term debt to total assets (negative), liquid asset to total assets (negative), size (negative), and basic profit ratio per share (positive); 2) Although each of these four factors impact directional connectedness of both from others and to others, they affect the latter ("to others") more than the former ("from others"), and thus, also affect net total directional connectedness; 3) More interestingly, compared to the macroeconomic factors presented in Table 7, firm-specific factors have much more explanatory power (adjusted R2) with regard to the total directional connectedness to others (and thus, net total directional connectedness), while macroeconomic factors bear more influence in determining total directional connectedness from others for the transmission of financial shocks. Obviously, the above analysis is preliminary. Further research is needed to examine the issue in more depth.

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)		
$Size_{(market\ value,\ RMB,\ log)}$	−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)
$Size_{(market\ value,\ RMB,\ log)}$	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.

CONCLUSIONS

This study explores the transmission of financial shocks among China's FIs using stock return data while controlling for interactions with the financial sectors of the four major global economies (i.e., the US, the UK, Germany, and Japan). Based on the newly developed network analysis, we document several novel findings of China's financial system. In particular, although banks still dominate China's financial system, nonbank FIs also bear considerable influence in the transmission network of financial shocks, thus confirming the recent growing concerns about China's shadow banking problems (e.g., Allen et al., 2012). Interestingly, the market oriented large commercial banks played a more pronounced role than the Big Four in the financial shock transmission network during the sample period. The role that each FI plays during the transmission of financial shocks also varies over time. Furthermore, China's financial sector exerts considerable influence on financial sectors in major developed countries, especially Japan. Macroeconomic factors, especially currency-related factors, mainly determine the degree of influence from other institutions on a particular FI while firm-specific factors mainly determine the degree of influence of a particular FI on others during the transmission of financial shocks.

The findings of this study suggest the need to reconsider the conventional approach of identifying SIFIs based on relatively low frequency financial data (e.g., IMF, BIS, and FSB, 2009; Allahrakha et al., 2015; Glasserman and Loudis, 2015). Such an approach could fail to capture the time-varying role that each institution may play in the transmission network of financial shocks, at least in China. The documented pattern of interconnectedness between

China and the financial sectors of the other four major global economies also implies that any policy intervention in the financial sector of a major country may spill over to the financial sectors in other countries. Accordingly, some international policy coordination involving China is warranted. Finally, to achieve efficient financial regulation and supervision in China, we must be more attentive to the emerging impact of nonbank FIs (Allen et al., 2012).

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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.

	SIT	SLS	GYS	HTS	PS	CJS	CS	NES	PAI	CLI	CPI	HXB	BOC	BON	CMB	IB	ICBC	BN	PAB
SIT	10	3.4	4.2	3.8	4.1	4.3	4	4.4	3	2.7	3.1	2.3	1.1	2.8	1.8	2.3	1.2	3.1	2.6
SLS	3.2	9.3	4.9	4.3	4.7	4.6	4.6	5	2.9	2.6	2.7	2	1	2.3	1.8	2.2	1.1	2.5	2.2
GYS	3.1	3.9	7.5	4.5	4.2	4.9	4.6	4.9	2.9	2.8	3.1	2.2	1	2.7	1.8	2.2	1.2	2.7	2.4
HTS	2.5	3.1	4	6.6	3.7	4.2	5.4	4	3.3	2.7	3.2	2.5	1.4	2.4	2.4	2.7	1.5	2.5	2.6
PS	3.2	3.9	4.4	4.4	7.8	4.8	4.7	4.8	2.8	2.5	2.7	2.2	1.1	2.4	1.9	2.2	1.2	2.7	2.3
CJS	3	3.5	4.7	4.6	4.4	7.1	4.8	4.8	2.8	2.5	2.7	2.3	1.1	2.4	1.9	2.3	1.3	2.7	2.5
CS	2.6	3.1	3.9	5.2	3.8	4.3	6.4	4	3.4	2.8	3.2	2.5	1.4	2.5	2.3	2.7	1.5	2.6	2.7
NES	3.2	3.9	4.8	4.5	4.5	5	4.6	7.3	2.9	2.5	2.8	2.2	1.1	2.4	1.8	2.3	1.2	2.7	2.5
PAI	2	2	2.6	3.3	2.4	2.6	3.5	2.6	6.7	4.5	4.9	3.5	2.2	2.9	3.3	3.4	2.2	3	3.2
CLI	2	2.1	2.7	3.1	2.3	2.6	3.3	2.5	5	7.4	5.5	3.2	2.5	3	3.1	3.1	2.3	3.1	2.9
CPI	2.1	2	2.9	3.4	2.4	2.6	3.5	2.6	5.1	5.1	6.9	3.2	2.3	3	3.2	3.1	2.3	3	3
HXB	1.5	1.3	1.9	2.5	1.8	2	2.5	1.9	3.3	2.7	3	6.3	3	4	4.3	4.5	3.1	4	4.1
BOC	1	0.9	1.2	1.8	1.3	1.4	1.8	1.3	2.9	3	2.9	4.1	8.7	3.1	3.8	3.6	5.4	3.6	3.2
BON	1.8	1.7	2.4	2.5	2.1	2.3	2.6	2.2	3	2.8	2.9	4.2	2.4	6.8	3.5	4.2	2.6	5	3.9
CMB	1.2	1.4	1.7	2.5	1.7	1.9	2.5	1.7	3.5	2.9	3.3	4.6	3.1	3.6	6.9	4.4	3.3	3.8	3.8
IB	1.5	1.5	1.9	2.6	1.8	2.1	2.6	2	3.2	2.6	2.9	4.5	2.7	3.9	4	6.3	2.9	4.1	4.5
ICBC	1.1	1	1.4	1.9	1.4	1.6	1.9	1.4	2.9	2.7	2.9	4.1	5.3	3.3	3.9	3.8	8.5	3.4	3.3
BN	2	1.7	2.3	2.5	2.2	2.5	2.7	2.3	2.9	2.7	2.8	4.1	2.7	4.8	3.5	4.2	2.6	6.5	4
PAB	1.7	1.6	2.2	2.7	1.9	2.3	2.8	2.2	3.2	2.6	2.9	4.3	2.4	3.8	3.6	4.7	2.6	4.1	6.7
MSB	1.3	1.1	1.6	2.2	1.5	1.8	2.1	1.6	3.3	2.9	3	4.8	3.1	3.7	4.5	4.9	3.2	3.8	4.4
CCB	1.1	1	1.6	2.2	1.5	1.7	2.1	1.7	3.1	2.8	3	4.2	4.8	3.4	3.7	3.6	4.9	3.4	3.3
CB	1.2	1.2	1.5	2.3	1.5	1.8	2.5	1.6	3	2.8	2.7	4.4	3.8	3.7	3.8	4.2	3.1	4.1	3.9
BB	1.6	1.3	1.8	2.3	1.8	2.1	2.4	1.8	3.2	2.8	3.1	4.4	2.9	4.1	4.1	4.5	2.9	4.2	4
BC	1.3	1.1	1.6	2.1	1.6	1.9	2.2	1.7	3.1	2.9	3	4.2	4.1	3.6	3.9	4	3.9	4	3.6
PDB	1.4	1.5	1.9	2.6	1.9	2.1	2.6	2	3.2	2.6	2.8	4.6	2.6	3.9	4.3	4.8	2.7	3.9	4.2
USF	0.3	0.2	0.3	0.4	0.5	0.3	0.4	0.2	0.4	0.3	0.5	0.9	0.1	0.7	0.7	0.7	0.4	0.6	0.5
UKF	0.5	0.5	0.5	0.5	0.4	0.5	0.6	0.5	1	0.8	1	1.3	0.4	0.8	1.1	1	0.8	0.8	0.9
JPF	0.3	0.9	0.9	1	0.9	0.9	1.2	0.7	1.6	1.1	1.4	1.4	0.6	1.2	1.8	1.3	1	1.1	1.1
GMF	0.4	0.2	0.3	0.3	0.3	0.2	0.3	0.2	0.5	0.4	0.5	0.6	0.1	0.4	0.7	0.6	0.3	0.5	0.6
HuaT	2.7	3.2	4	4.6	3.8	4.2	4.6	4.1	3	2.7	3	2.5	1.5	2.6	2.2	2.6	1.7	2.7	2.6
GFS	2.9	3.4	4.3	4.7	3.9	4.6	4.8	4.5	3.1	2.7	3	2.3	1.2	2.4	2	2.4	1.4	2.6	2.6
CMS	2.7	3.1	3.9	4.7	3.8	4.3	4.7	4	3	2.7	2.9	2.5	1.4	2.7	2.3	2.6	1.7	2.7	2.8
IS	2.8	3.6	4.2	4.6	4.5	4.7	4.6	4.5	3	2.7	3	2.2	1.2	2.5	1.9	2.4	1.4	2.6	2.4
ES	2.8	3.5	4.5	4.5	3.9	4.4	4.5	4.5	2.9	2.6	2.8	2.4	1.3	2.7	1.9	2.5	1.4	2.8	2.6
AB	1.2	1	1.4	1.9	1.5	1.7	2	1.5	3	2.7	2.8	4	5.3	3.2	3.8	3.9	5.1	3.5	3.5
EB	1.3	1.2	1.6	2.2	1.7	1.8	2.3	1.7	3.2	2.9	2.9	4.4	3.9	3.8	3.8	4.2	3.5	4.1	3.7
TO	65	70	90	103	86	95	106	92	103	91	99	109	76	101	99	108	79	106	102
NET	−25	−21	−2	10	−6	2	12	−1	10	−2	6	15	−15	8	6	14	−12	12	9

	MSB	CCB	CB	BB	BC	PDB	USF	UKF	JPF	GMF	HuaT	GFS	CMS	IS	ES	AB	EB	From
SIT	1.7	1.5	1.5	2.2	2	2.1	0.1	0.2	0	0.1	4.3	4.5	4.1	4	4.2	1.6	2	90
SLS	1.4	1.3	1.4	1.7	1.5	2.1	0.1	0.2	0.1	0	4.8	4.8	4.4	4.8	4.8	1.3	1.7	91
GYS	1.6	1.5	1.4	1.9	1.8	2.1	0.1	0.1	0.1	0.1	4.7	4.8	4.5	4.5	5	1.4	1.8	92
HTS	1.9	1.9	1.8	2.1	2.1	2.5	0.1	0.1	0.1	0.1	4.8	4.7	4.7	4.3	4.3	1.7	2.2	93
PS	1.5	1.5	1.4	1.9	1.9	2.1	0.1	0.1	0.1	0	4.7	4.6	4.5	5	4.5	1.5	2	92
CJS	1.7	1.6	1.6	2.1	2	2.2	0.1	0.1	0.1	0	4.7	4.9	4.6	4.8	4.7	1.5	2	93
CS	1.8	1.8	2	2.1	2.1	2.5	0.1	0.1	0.1	0	4.7	4.7	4.6	4.2	4.3	1.7	2.2	94
NES	1.5	1.6	1.5	1.9	1.8	2.1	0.1	0.1	0.1	0	4.8	5	4.5	4.7	4.9	1.5	1.9	93

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: measuring the connectedness of financial firms. J. Econ. 182, 119–134.

Hao, X., Shi, J., Yang, J., 2014. The differential impact of the bank–firm relationship on IPO underpricing: evidence from China. Pac. Basin Financ. J. 30, 207–232.

Helwege, J., Zhang, G., 2015. Financial firm bankruptcy and contagion. Review of Finance 20, 1321–1362.

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

Huang, T.-H., Lin, C.-I., Chen, K.-C., 2017. Evaluating efficiencies of Chinese commercial banks in the context of stochastic multistage technologies. Pac. Basin Financ. J. 41, 93–110.

Imai, M., Takarabe, S., 2011. Bank integration and transmission of financial shocks: evidence from Japan. Am. Econ. J. Macroecon. 3, 155–183.

IMF. 2011. Global Economic Prospects and Policy Challenges.

IMF, BIS, FSB, 2009. Guidance to Assess the Systematic Importance of Financial Institutions, Markets and Instruments: Initial Considerations, The Report to the G20 Finance Ministers and Governors.

Jach, A., 2017. International stock market Comovement in time and scale outlined with a thick pen. J. Empir. Financ. 43, 115–129.

Jarrow, R.A., Yu, F., 2001. Counterparty risk and the pricing of defaultable securities. J. Financ. 56, 1765–1799.

Kamber, G., Thoenissen, C., 2013. Financial exposure and the international transmission of financial shocks. J. Money Credit Bank. 45, 127–158.

Kilian, L., Lütkepohl, H., 2017. Structural Vector Autoregressive Analysis. Cambridge University Press.

Lee, C.-C., Hsieh, M.-F., 2013. Beyond bank competition and profitability: can moral hazard tell us more? J. Financ. Serv. Res. 44, 87–109.

Li, X., Yu, H., Fang, L., Xiong, C., October 2019. Do firm-level factors play forward-looking role for financial systemic risk: evidence from China. Pac. Basin Financ. J. 57, 101074.

Mistrulli, P.E., 2011. Assessing financial contagion in the interbank market: maximum entropy versus observed interbank lending patterns. J. Bank. Financ. 35, 1114–1127.

Pang, K., Siklos, P.L., 2016. Macroeconomic consequences of the real-financial nexus: imbalances and spillovers between China and the US. J. Int. Money Financ. 65, 195–212.

Peek, J., Rosengren, E.S., 1997. The international transmission of financial shocks: the case of Japan. Am. Econ. Rev. 495–505.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Econ. Lett. 58, 17–29.

Schnabl, P., 2012. The international transmission of bank liquidity shocks: evidence from an emerging market. J. Financ. 67, 897–932.

Tobin, D., Volz, U., 2018. The Development and Transformation of the People's Republic of China's Financial System. Asian Development Bank Institute working paper No. 825.

Yang, J., Zhou, Y., 2013. Credit risk spillovers among financial institutions around the global credit crisis: firm-level evidence. Manag. Sci. 59, 2343–2359.

Yang, J., Hsiao, C., Li, Q., Wang, Z., 2006. The emerging market crisis and stock market linkages: further evidence. J. Appl. Econ. 21, 727–744.

Yang, L., van Wijnbergen, S., Qi, X., Yi, Y., 2019. Chinese shadow banking, financial regulation and effectiveness of monetary policy. Pac. Basin Financ. J. 57, 101–169.

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