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Frequency volatility connectedness across different industries in China

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Abstract

Utilizing the advantageous method of Barunik and Krehlik (2018), we examine the frequency connectedness of equity volatilities across 12 industries in China from October 2003 to April 2018. The results indicate that the main targets of risks in China are Banking and Real Estate, while the main sources of risks are Construction and Materials, Industrial Transportation, and Chemicals. The study also highlights the importance of the use of frequency connectedness method such that the main targets and sources of risks at different frequencies over different time periods can be detected, providing essential information for the monitoring of the financial market.

Keywords: Frequency Volatility Connectedness; Volatility Spillovers; Chinese Industries

JEL classification: G10, G15

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1. Introduction

After four decades of fast economic growth, China is nowadays the second largest economy in the world with an increasingly central role for the global economy. Recent literature shows that certain Chinese industries such as Banking and manufacturing-related industries are perceived to have significant implications for the global financial and economic stability. For example, Alessandri et al. (2015) find that after the Global Financial crisis, global systemically important banks shifted from the developed economies to the emerging economies, particularly China. This finding implies that the Banking industry in China has become an important part of the global financial system. In similar vein, Baum et al. (2015) show that macroeconomic announcements related to Chinese manufacturing and industrial output (purchasing manager index, industrial production, and real GDP) are viewed as barometers of the state of the world economy, affecting equity, commodity, and currency markets. Furthermore, recent literature also suggests that intersectoral linkages of Chinese industries are of high importance for maintaining its own financial and economic stability. For instance, Chan et al. (2016) show that due to intersectoral linkages, Real Estate sector has large credit risks spillovers to 13 other sectors in China and contributes significantly to the economic output.

The purpose of this study is to examine which Chinese industries are the main sources of risks and which are most susceptible targets of risks in terms of equity volatility connectedness. Equity volatility connectedness can be used to show which industries are the main receivers of volatility spillovers (i.e. the main targets of risks) and which industries are the main transmitters of volatility spillovers (i.e. the main sources of risks) from the perspective of market participants. This is an important task, given the significant role of certain industries in China (e.g., Banking and manufacturing-related industries). For this purpose, we use an advantageous approach of Barunik and Krehlik (2018) and analyze the equity volatility connectedness at different frequencies (short, medium, and long term), which is important for portfolio construction, risk management, and the monitoring of financial risks. For instance, for portfolio construction, investors with (short) long investment horizons may focus on the (short-term) long-term volatility connectedness between two industries. In addition, high long-term volatility connectedness across different industries suggests that shocks to the industries are persistent and have long-term impact on the system. Hence, for monitoring financial risks, policy makers should pay more attention to shocks that cause jumps in long-term volatility connectedness across industries, as those shocks create large long-term impact on the system.

There is increasing number of studies that examine the connectedness of volatilities across different financial markets or financial institutions (e.g. international stock markets, Diebold and Yilmaz, 2009; sovereign bond markets, Fernandez-Rodriguez et al., 2016; cryptocurrencies, Koutmos, 2018; financial institutions, Diebold and Yilmaz, 2016). Recent studies have also documented the connectedness of economic uncertainties across countries (Antonakakis et al. 2018; Gabauer and Gupta 2018). However, studies that analyze the connectedness at different frequencies are very limited. The most recent studies in the area of frequency connectedness (Ferrer et al., 2018; Tiwari et al., 2018; and Wang and Wang, 2019) utilize the novel method of Barunik and Krehlik (2018).

Previous studies on the connectedness among assets in China are relatively limited. An essential contribution to the Chinese sectoral connectedness topic is study of Wang and Wang (2019). They investigate the frequency volatility spillovers between crude oil and Chinese sectoral equity markets and find that short-term spillovers are the main drivers of total volatility spillovers. In the similar line of research, Chan et al. (2016) provide an extensive analysis of links of Real Estate sector with other sectors in China, but they exclude the financial sectors and do not examine frequency connectedness. Some other recent studies include Wang et al. (2018) who examine the volatility connectedness of the Chinese banking system, Wang et al. (2018) who analyze the connectedness of the financial institutions in China, and Zhang and Fan (2019) who study the connectedness of China's urban housing prices.

This study complements previous studies on the connectedness at different frequencies and extends the literature as follows: We are the first to investigate the frequency connectedness of equity volatilities across different industries by applying a novel method of Barunik and Krehlik (2018, hereafter BK) and we also account for the potential breakpoints of the volatility connectedness by applying the Bai-Perron test (Bai and Perron 1998). Our focus is on the industries in China, since recent literature pointed out that certain Chinese industries such as Banking and manufacturing-related industries play important roles in the global financial and economic stability. Two most closely related studies are Wang and Wang (2019) and Chan et al. (2016). Our study differs from Wang and Wang (2019) in that we consider the connectedness among the Chinese sectoral equity markets, whereas Wang and Wang (2019) focus on the connectedness between crude oil prices and Chinese sectoral equity markets and do not analyze the connections among the various sectoral equity markets. Compared with the study of Chan et al. (2016) that excludes all the financial sectors, our study also includes the sector of Banks, which is an important sector from the perspective of risk connectedness/spillovers in an economy. After the Global Financial crisis, there was a shift of global systemically important banks from the developed economies to the emerging economies, particularly China (Alessandri et al. 2015). Hence, it is interesting to see whether the connectedness pattern for the Chinese banking sector changed after the shift in the global systemically important banks. Our study also differs from Chan et al. (2016) in that we focus on the equity volatility of the industries rather than the credit risk, and we distinguish the connectedness among the industries at different frequencies over different time periods. This distinction may be important, as our results show that the importance of an industry as a target or source of risks depends on the frequency and time period. In addition, by accounting for the breakpoints of volatility connectedness, our study enables identifying important subperiods (such as periods of subprime crisis and European debt crisis) in which volatility connectedness changes, shedding light on the underlying frequency sources of volatility connectedness and systemic risk during these subperiods.

2. Data and method

Our dataset includes the daily high, low, opening, and closing equity indexes of 12 industries in China (data is obtained from Datastream). Based on the industry classifications of listed firms by China Securities Regulatory Commission, there are 19 industries (the highest-level classifications). We select industries from the FTSE CHINA 600 industries in Datastream that match these 19 industries.[1] The 12 matched industries are Mining, Auto and Parts, Chemicals, Electricity, Construction and Materials, General Retailers, Industrial Transportation, Software and Computer Services, Banks, Real Estate, Health Care, and Media. The sample period of the study ranges from October 8, 2003 to April 30, 2018. In this study, we utilize the methodology of Garman and Klass (1980) to obtain daily range-based volatility estimate.[2] The volatility estimate is then transformed into log volatility.

For the method, we employ the frequency domain connectedness measure of BK which is built on the idea of Diebold and Yilmaz (2012; hereafter DY). DY construct the connectedness measures based on the generalized forecast error variance decompositions (GFEVD). Taking into account the heterogeneous frequency responses to economic shocks, BK extend the DY connectedness and develop connectedness measures based on the spectral representation of GFEVD. BK frequency connectedness decomposes the DY connectedness into separate parts that in sum give the original DY connectedness

[1] As Real Estate industry is not one of the 42 FTSE CHINA 600 industries in Datastream, we use the equity index of Shenzhen Real Estate to represent the Real Estate industry. Since there are many sub-industries for the industry of Manufacturing, two sub-industries are included to represent the industry of Manufacturing: Auto and Parts and Chemicals.

[2] Range-based volatility estimate for a given day is $\tilde{\sigma}^2 = 0.511(h-l)^2 - 0.019[(c-o)(h+l-2o) - 2(h-o)(l-o)] - 0.383(c-o)^2$, where h, l, o, and c are the log daily high price, log daily low price, log opening price, and log closing price, respectively.

and reveal the frequency sources of the connectedness (For technical details, see Appendix). In the empirical analysis, we focus on the frequency bands up to 1 week (or 5 days), 1 week to 1 month (or 20 days), and 1 month to 1 year (or 250 days), which corresponds to our short-, medium-, and long-term frequency connectedness, respectively.

3. Results

Figure 1 shows the overall DY and BK connectedness.[3] Among the four connectedness measures, short-term BK connectedness shows the largest fluctuations. Overall DY connectedness showed large decrease at the end of the sample period, which was caused by the initial decrease of long-term BK connectedness followed by the decrease of short-term BK connectedness. Short-term BK connectedness increased significantly from May 2010 to the end of 2011, resulting in the increase of overall DY connectedness during the European debt crisis. Thus, market participants in China appear to expect the shocks during the European debt crisis to have short-term impact.

Figure 2 displays the connectedness FROM all the other industries to each of the industries. The FROM connectedness showed similar trend to the overall connectedness. Compared to the overall and FROM connectedness, connectedness from each of the industries TO all the other industries were more volatile during the sample period (see Figure 3). Figures 1 to 3 show that short-term BK connectedness is generally larger than the medium- and long-term BK connectedness over the sample period. This result suggests the dominating role of short-term component for the frequency dependent connectedness

[3] Volatilities of the selected industries appear to be stationary and have kurtosis value close to that of normal distribution (see Table A1 in the appendix for the descriptive statistics of the volatilities of the selected industries). We estimate the dynamic connectedness with a rolling window of 1 year (250 days) and set the vector auto-regression order to 3 and forecast horizon to 100 days. We obtain very similar trend for the overall DY and BK connectedness, when we change the vector auto-regression order to 2, 4, or 5, or the forecast horizon to 80 or 120 (results available upon request). For the static (full-sample) DY and BK connectedness, see Tables A2, A3, A4, and A5 in the appendix.

measures, which is in line with the finding of Ferrer et al. (2018) and Wang and Wang (2019). Figure 4 shows the difference between the TO connectedness and FROM connectedness (i.e., the net total directional connectedness). Over the sample period, Banking industry was mostly a net volatility receiver, and the industry of Construction and Materials and the industry of Industrial Transportation were mostly net volatility transmitters.

To account for the potential breakpoints of the volatility connectedness, we apply the Bai-Perron test to the overall DY connectedness. Bai-Perron test suggests four breakpoints or five sub-periods over the sample period: 26.10.2004-18.4.2007, 19.4.2007-25.1.2011, 26.1.2011-19.2.2013, 20.2.2013-7.4.2015, and 8.4.2015-30.4.2018. The second and the third sub-period may correspond to the Global Financial crisis and European debt crisis, respectively. For each sub-period, we calculate the average net pairwise directional connectedness among the industries and present the results in Figures 5 to 9. Figure 5 shows that for the aggregate DY and disaggregate medium- and long-term BK connectedness, Banking industry was the main receiver of volatility connectedness before the Global Financial crisis, with net pairwise connectedness coming from Industrial Transportation and Construction and Materials to Banking industry. In contrast, for the short-term BK connectedness arising from the short-term impact of shocks, Media and Real Estate industries were the main receivers of volatility connectedness.

Figure 6 shows that for all the connectedness measures, during the Global Financial crisis, there was large volatility connectedness transmitted to the Banking industry and Real Estate industry, particularly from the industry of Construction and Materials and the industry of Industrial Transportation. In addition, there was also significant volatility connectedness from Chemicals to other industries in the short-run. These results are in line with the Baum et al. (2015) who demonstrate that the economic figures for manufacturing and industrial output are considered as the barometers of the state of the world economy. Analogously, during the European debt crisis, Banks and Real Estate were still the major receivers of volatility connectedness (see Figure 7). However, the major sources of risks were different at different frequencies; for the shocks with short-term impact, the major sources of risks were the industries of Construction and Materials, Chemicals, and Industrial Transportation; for the shocks with medium-term impact, the major sources of risks were the industries of Chemicals and Health Care; for the shocks with long-term impact, the major source of risks was the Media industry.

During the fourth sub-period from 20.2.2013 to 7.4.2015, Construction and Materials and Chemicals were the main sources of volatility connectedness, while the main receivers of volatility connectedness were different at different levels of frequencies (see Figure 8). For instance, Software and Computer services was the main receiver at short and medium term, while for long term Real Estate was the largest receiver. In contrast, during the last sub-period from 8.4.2015 to 30.4.2018, Banking industry was the main receiver of volatility connectedness, with different sources of risks at different levels of frequencies (see Figure 9). More specifically, Chemicals was the main source of short and medium term volatility connectedness, while Industrial Transportation was the largest source of long term volatility connectedness.

The above analysis indicates that the main targets of risks in China are Banking and Real Estate, while the main sources of risks are Construction and Materials, Industrial Transportation and Chemicals. These findings are consistent with those of Baum et al. (2015) and Chan et al. (2016). Studying the non-financial sectors, Chan et al., (2016) find that the Real Estate-Construction sector in China contributes significantly to the overall economic output, while Baum et al. (2015) show that figures related to Chinese manufacturing and industrial output are of particular importance. Overall, the results of the study provide interesting insight into which industries may be essential for maintaining financial stability over different time periods and at different frequency levels.

4. Conclusions

Recent research indicates that certain sectors of the Chinese economy have an increasingly important role in the world economy. In this light, we contribute to the literature by examining the volatility connectedness across different industries in China. For that purpose, we use the BK frequency connectedness method, which is advantageous for identifying sources and targets of risk within intersectoral framework. Specifically, it shows whether the volatility connectedness results from the short-, medium-, or long-term impact of shocks and thus reveals the underlying frequency sources of volatility connectedness. This is important, given that different agents may be interested in different level of connectedness: short-term investors may be interested in the high frequency pairwise connectedness between firms or industries, while policy makers may be concerned with the low frequency system-wide connectedness.

The results of our study show that before the Global Financial crisis, Banking industry in China was the major target of risks at medium and low frequencies, while Real Estate industry was a main target of risks at high frequency. Furthermore, during the periods of the Global Financial and European debt crisis, both the Banking industry and the Real Estate industry were the main target of risks at all the frequency levels, while the industry of Construction and Materials and the industry of Industrial Transportation were important sources of risks. Overall, the study highlights the importance of the use of frequency connectedness method such that the main targets and sources of risks at different frequencies over different time periods can be identified, providing essential information for the monitoring of the financial market.

In this study, we only consider an industry as a direct target or source of risks for the case of China. However, an industry as a direct target of risks in China may be a source of risks to other industries in other countries; similarly, an industry as a direct source of risks in China could also result from the risks of other industries in other countries. Therefore, future research could take into account these indirect effects and study the frequency connectedness of equity volatilities across different industries in different countries.

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Figure 1. Overall connectedness. The solid line is the DY connectedness; the solid grey line is the short-term BK connectedness; the dashed line is the medium-term BK connectedness; the (lowest) dotted line is the long-term BK connectedness.

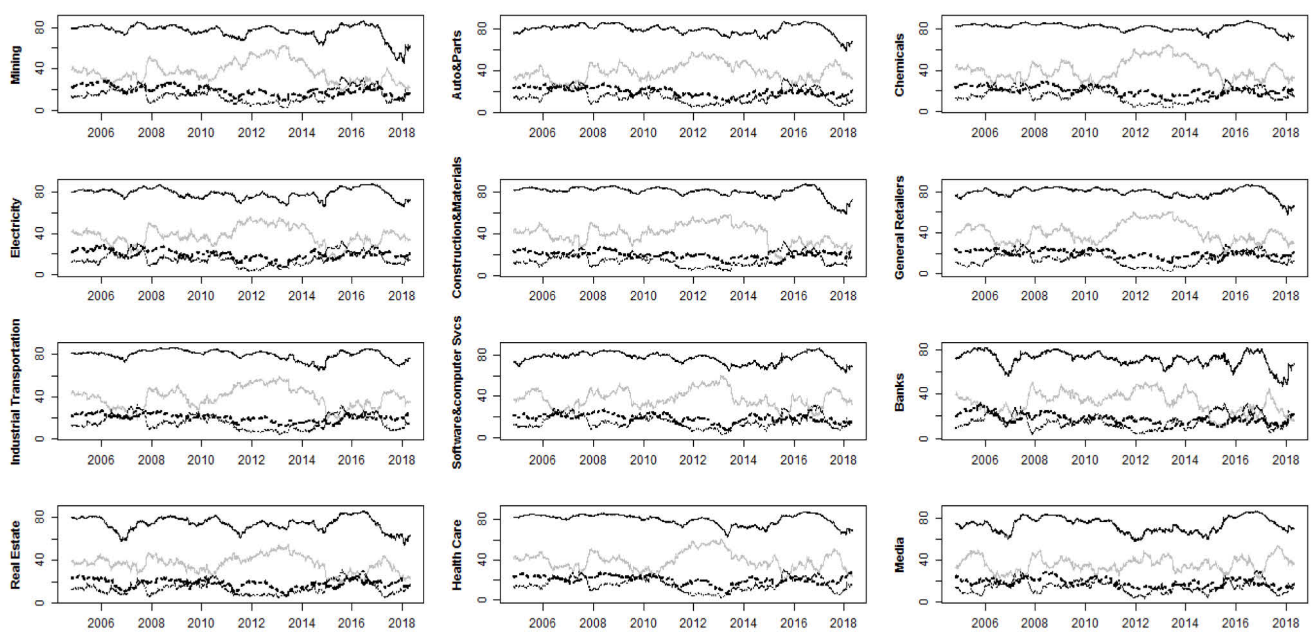

Figure 2. FROM connectedness. Each of the above graphs shows the dynamic connectedness from all the other industries to a given industry: the solid line is the DY connectedness; the solid grey line is the short-term BK connectedness; the dashed line is the medium-term BK connectedness; the (lowest) dotted line is the long-term BK connectedness.

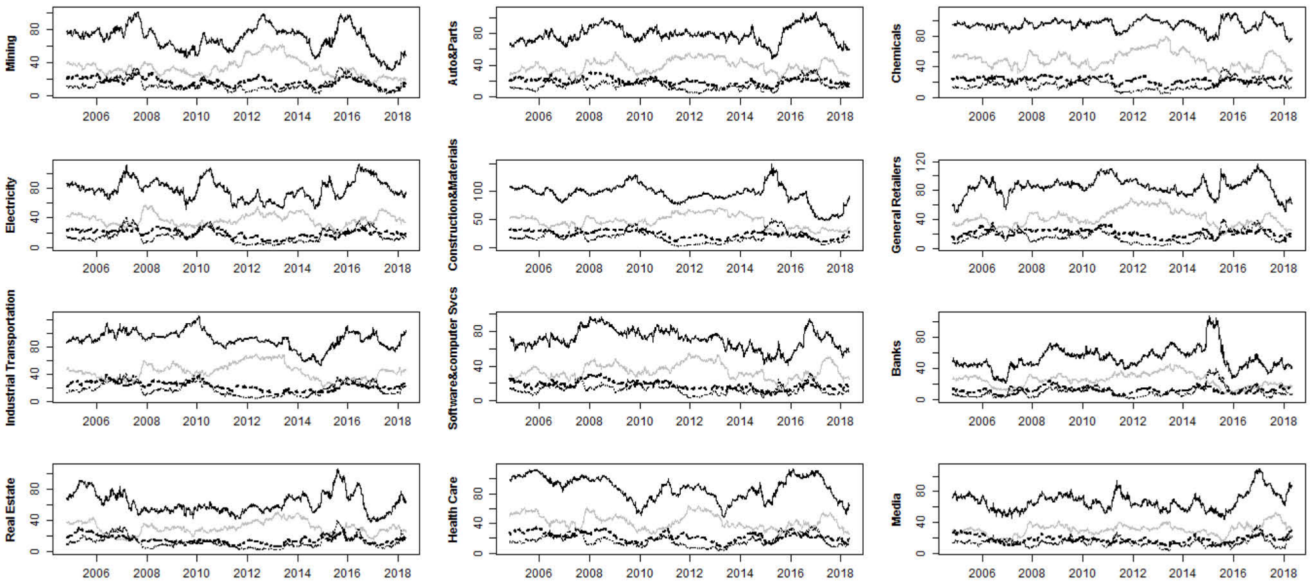

Figure 3. TO connectedness. Each of the above graphs shows the dynamic connectedness from a given industry to all the other industries: the solid line is the DY connectedness; the solid grey line is the short-term BK connectedness; the dashed line is the medium-term BK connectedness; the (lowest) dotted line is the long-term BK connectedness.

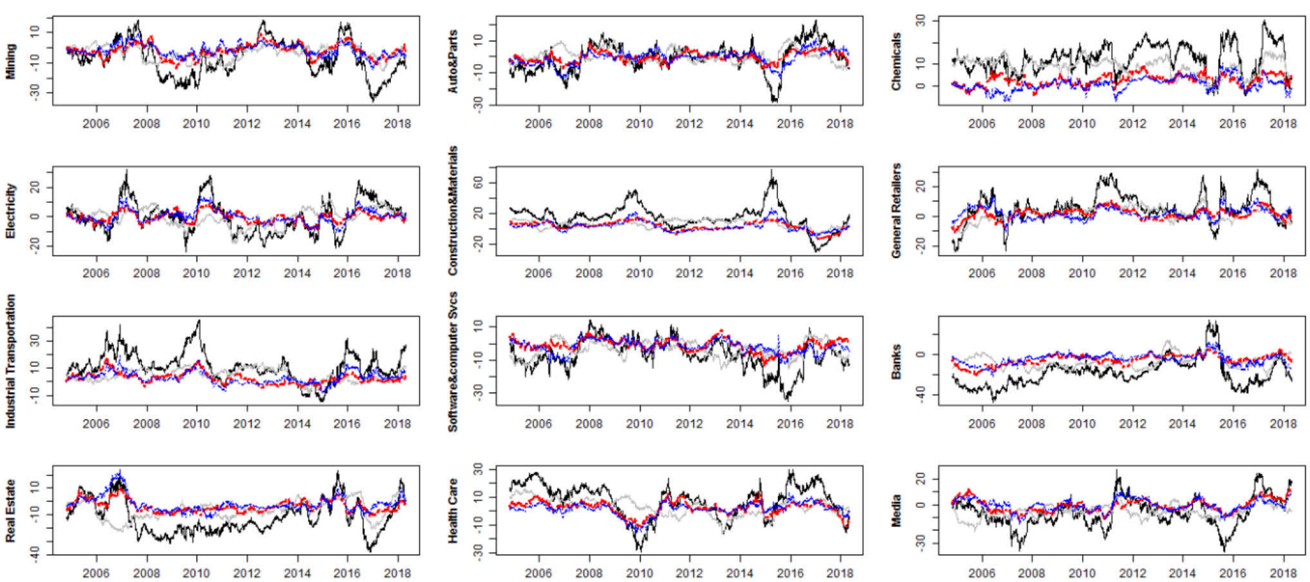

Figure 4. Net total directional connectedness. Each of the above graphs shows the dynamic net total directional connectedness from a given industry to all the other industries: the solid line is the DY connectedness; the solid grey line is the short-term BK connectedness; the dashed red line is the medium-term BK connectedness; the dotted blue line is the long-term BK connectedness.

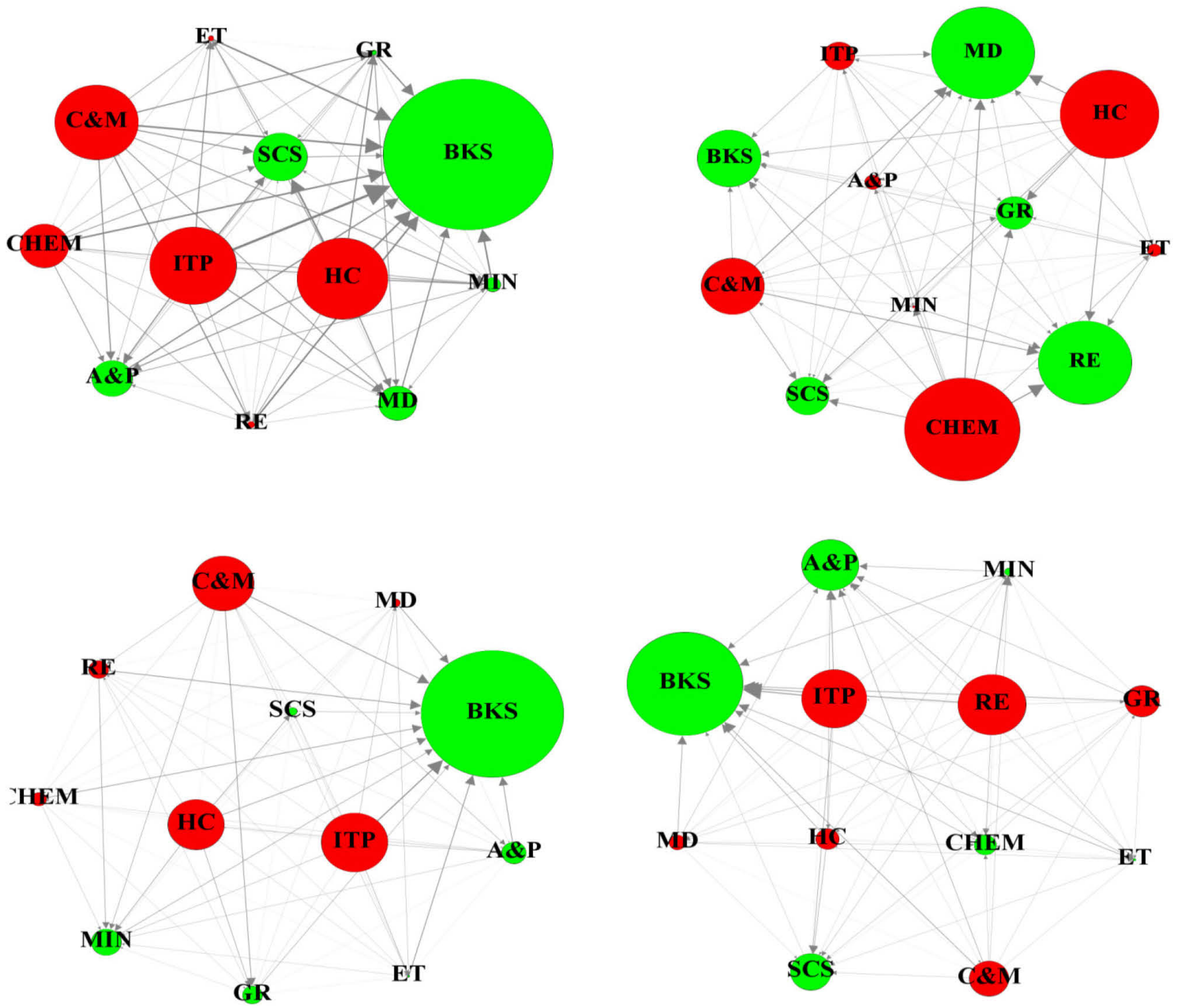

Figure 5. Average net pairwise directional connectedness from 26.10.2004 to 18.4.2007. The upper left graph is the DY connectedness; the upper right graph is the short-term BK connectedness; the lower left graph is the medium-term BK connectedness; the lower right graph is the long-term BK connectedness. An arrow from A to B shows that the average net pairwise directional connectedness from industry A to industry B is positive, and larger arrows represent relatively larger connectedness. In each graph, the size of a circle represents the relative size of the average net directional connectedness from an industry to all the other industries: when the average net directional connectedness from an industry to all the other industries is positive (negative), it is shown in red (green). Abbreviations of the industry names: Mining=MIN, Auto and Parts=A&P, Chemicals= CHEM, Electricity=ET, Construction and Materials=C&M, General Retailers=GR, Industrial Transportation=ITP, Software and Computer Services=SCS, Banks=BKS, Real Estate=RE, Health Care=HC, and Media=MD.

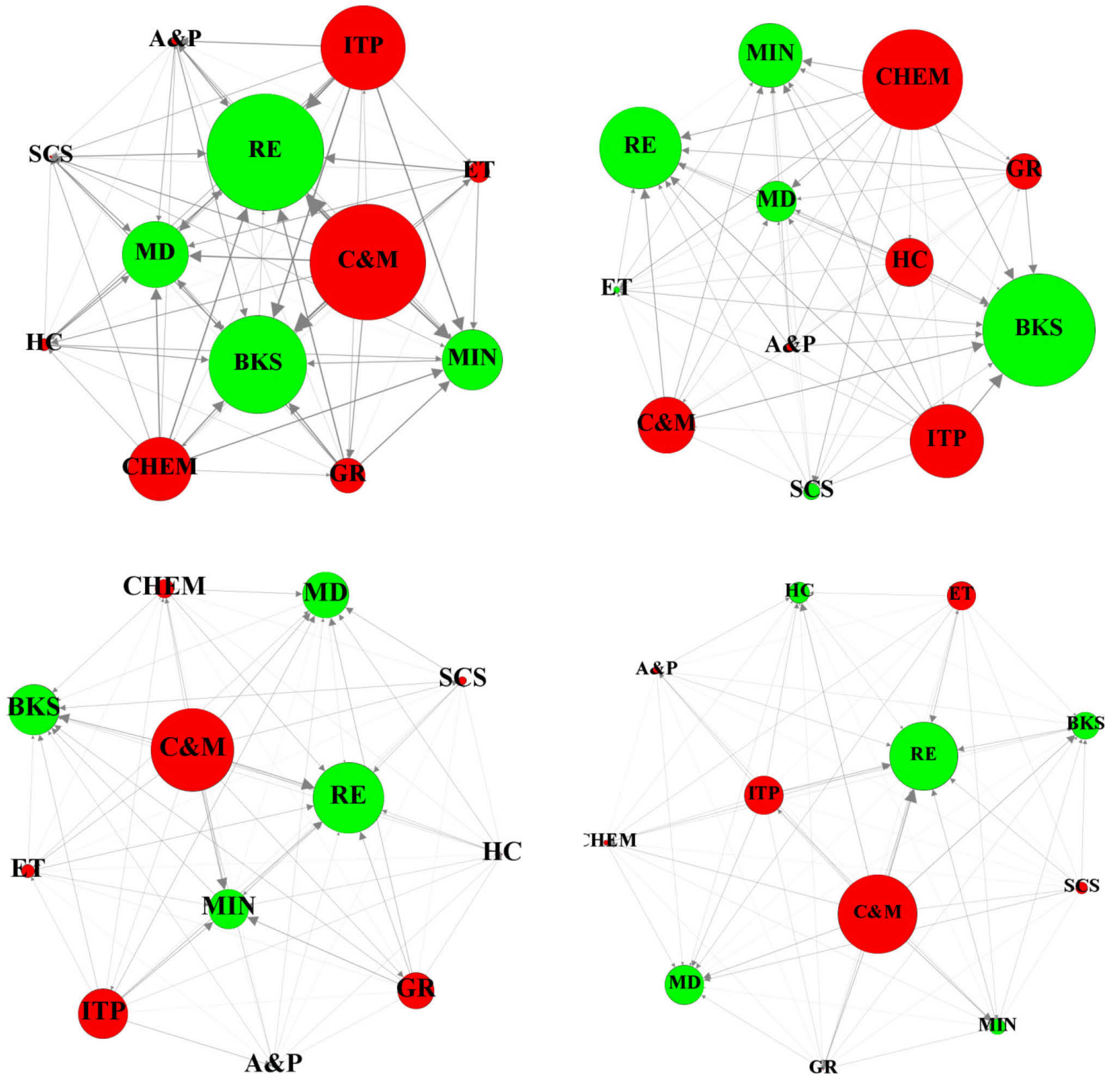

Figure 6. Average net pairwise directional connectedness from 19.4.2007 to 25.1.2011. Notes: see Figure 5.

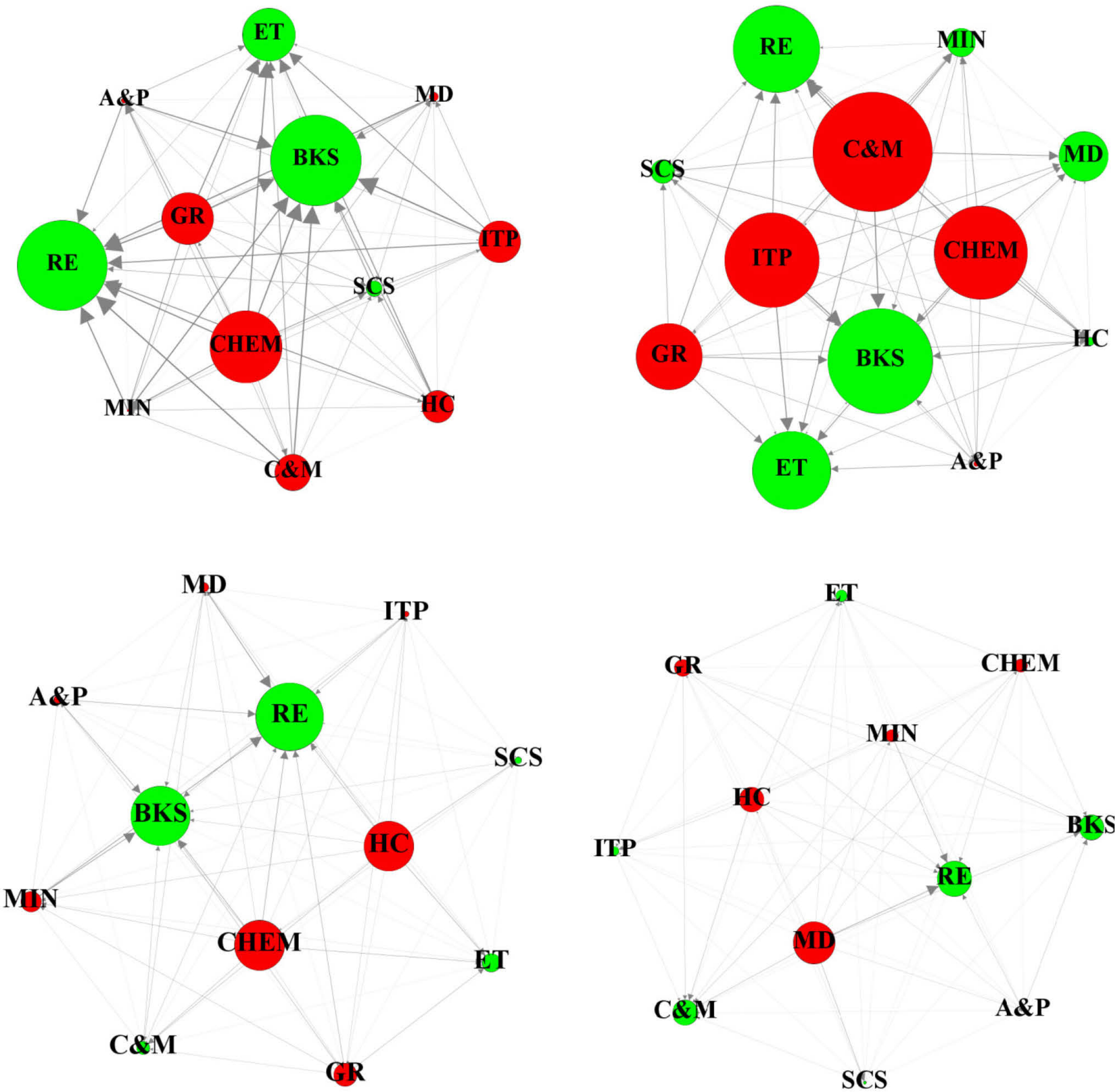

Figure 7. Average net pairwise directional connectedness from 26.1.2011 to 19.2.2013. Notes: see Figure 5.

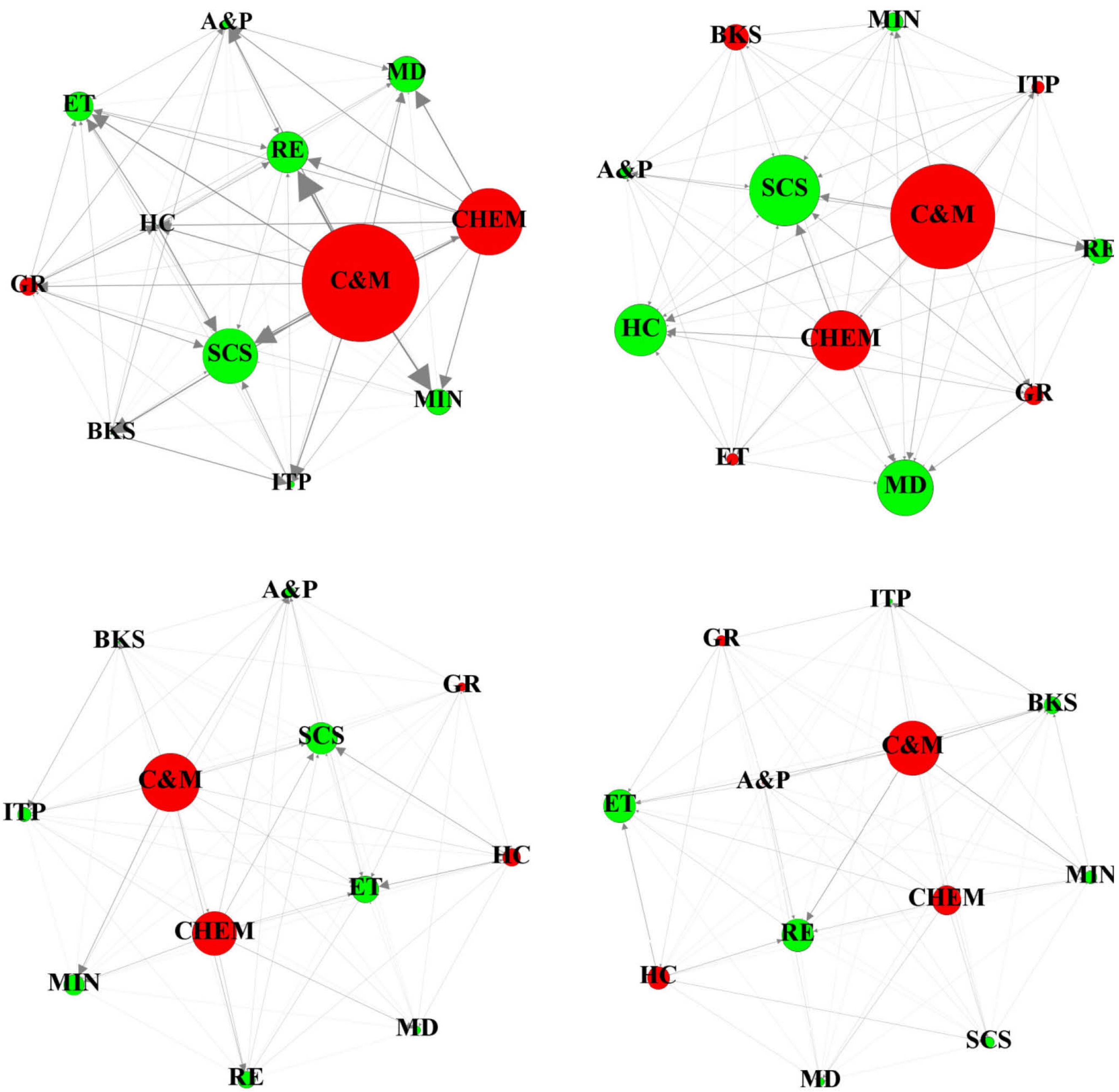

Figure 8. Average net pairwise directional connectedness from 20.2.2013 to 7.4.2015. Notes: see Figure 5.

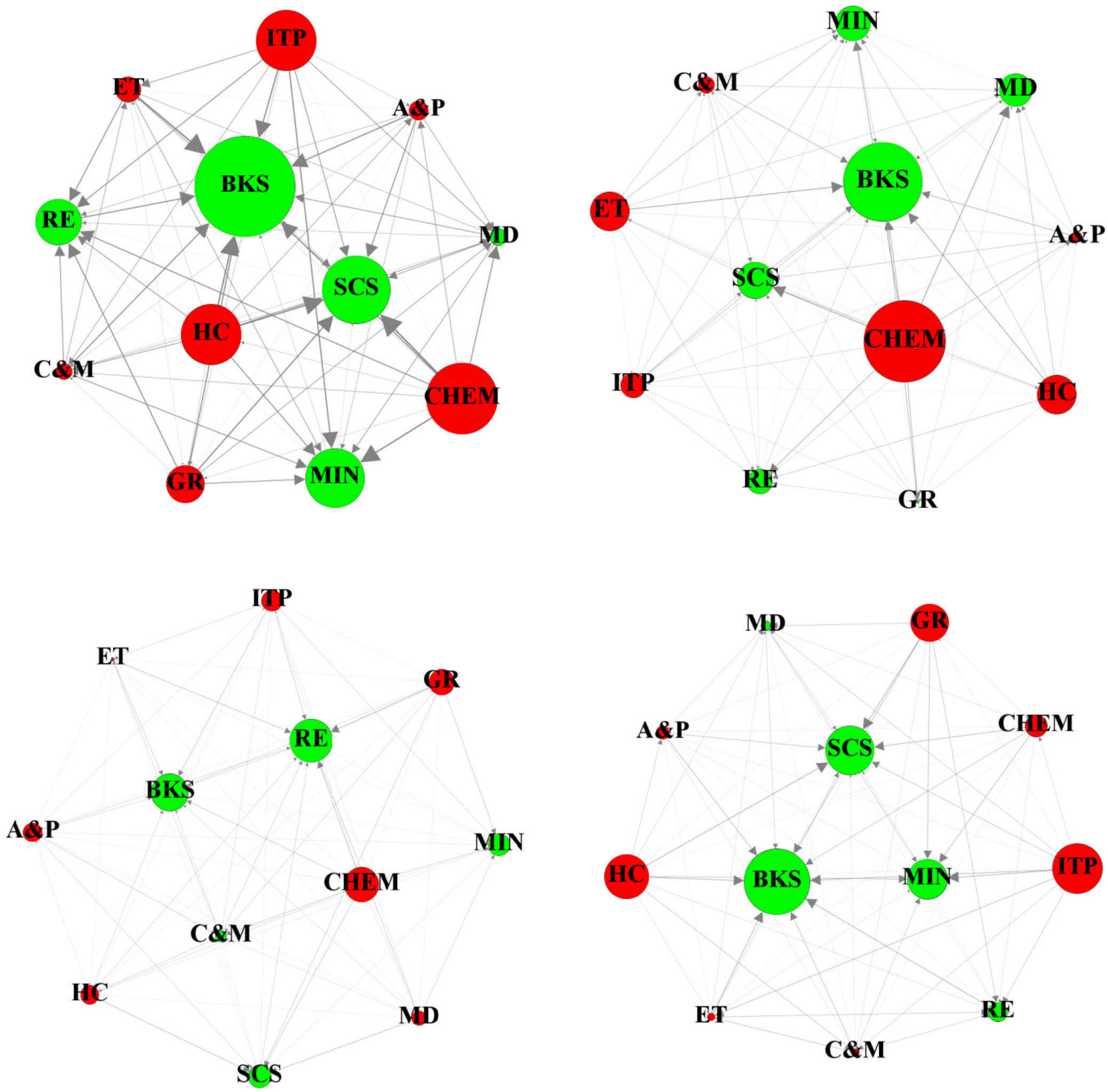

Figure 9. Average net pairwise directional connectedness from 8.4.2015 to 30.4.2018. Notes: see Figure 5.

Appendix

The frequency domain connectedness of Barunik and Krehlik (2018) may be briefly presented as below: let us assume that a n-variate vector z_t follows a covariance-stationary VAR(p) process with the following moving average VMA(∞) representation

$$z_t = \Omega(L) \in_t, \tag{1}$$

where $\Omega(L)$ and $\in_t$ respectively are $n \times n$ infinite lag polynomial matrix of VMA coefficients, and white-noise term. Following Diebold and Yilmaz (2012), the generalised forecast error variance decomposition (GFEVD) may be presented as below:

$$(\theta_H)_{j,k} = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H} \left((\Omega_h \Sigma)_{j,k} \right)^2}{\sum_{h=0}^{H} (\Omega_h \Sigma \Omega')_{j,j}}, \tag{2}$$

where $\sigma_{kk} = (\Sigma)_{k,k}$ (where Σ is the covariance matrix of white noise error terms) and Ω_h is a $n \times n$ matrix of VMA coefficients matching to lag h. The H-step ahead GFEVD of variable j due to shocks in variable k is represented by $(\theta_H)_{j,k}$. Following Barunik and Krehlik (2018), the frequency domain representation of Equation 2 may be presented as follows:

$$\left(f(\omega)\right)_{j,k} \equiv \frac{\sigma_{kk}^{-1} \left| \left(\Omega(e^{-iw})\, \Sigma\right)_{j,k} \right|^2}{\left(\Omega(e^{-iw})\, \Sigma \Omega'(e^{+iw})\right)_{j,j}}. \tag{3}$$

where $\Omega(e^{-iw}) = \sum_h e^{-iwh}\, \Omega_h$ presents a frequency response function using Fourier transform of Ω_h over generalised causation spectrum of frequencies $\omega = \in (-\pi, \pi)$. Further, $\left(f(\omega)\right)_{j,k}$ presents the percentage of the spectrum of variable j at frequency ω due to shocks in variable k which may be interpreted as a within frequency causation (Barunik and Krehlik 2018). Assuming a frequency band $g = (c, d): c, d \in (-\pi, \pi), c < d,$ the GFEVD on g is then defined as

$$\left(\theta_g\right)_{j,k} = \frac{1}{2\pi}\int_g \Gamma_j(\omega)\left(f(\omega)\right)_{j,k} g\omega. \tag{4}$$

where $\Gamma_j(\omega)$ represents the weighting function which is presented as follows:

$$\Gamma_j(\omega) = \frac{\left(\Omega\left(e^{-iw}\right)\Sigma\Omega'\left(e^{+iw}\right)\right)_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(\Omega\left(e^{-i\lambda}\right)\Sigma\Omega'\left(e^{+i\lambda}\right)\right)_{j,j} g\lambda}, \tag{5}$$

which is the power of variable j at a given frequency and sums through frequencies to 2π. Following Barunik and Krehlik (2018), the normalised GFEVD on the frequency band g may be writtes as follows:

$$\left(\tilde{\theta}_g\right)_{j,k} = \frac{\left(\theta_g\right)_{j,k}}{\Sigma_k\left(\theta_\infty\right)_{j,k}}, \tag{6}$$

where $\left(\theta_\infty\right)_{j,k}$ is the value of $\left(\theta_g\right)_{j,k}$ in Equation (4) when the frequency band is $\left(-\pi,\pi\right)$. Therefore, the frequency domain connectedness on the frequency band g may be presented as follows:

$$C_g^F = 100\left(\frac{\Sigma\left(\tilde{\theta}_g\right)_{j,k}}{\Sigma\left(\tilde{\theta}_\infty\right)_{j,k}} - \frac{\Sigma_{j=k}\left(\tilde{\theta}_g\right)_{j,k}}{\Sigma\left(\tilde{\theta}_\infty\right)_{j,k}}\right). \tag{7}$$

Table A1. Descriptive statistics of the log volatilities of the selected industries.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD
Mean	-4.30	-4.43	-4.51	-4.67	-4.46	-4.48	-4.61	-4.28	-4.52	-4.33	-4.64	-4.33
Max.	-2.47	-2.51	-2.62	-2.55	-2.52	-2.26	-2.48	-2.24	-2.50	-2.53	-2.60	-2.38
Min.	-6.10	-6.46	-6.45	-6.61	-6.00	-6.23	-6.17	-6.42	-6.58	-6.51	-6.70	-6.49
Std. Dev.	0.55	0.57	0.54	0.60	0.55	0.55	0.58	0.52	0.63	0.57	0.58	0.60
Skewness	0.16	0.11	0.18	0.26	0.36	0.22	0.33	0.11	-0.06	0.00	0.12	-0.18
Kurtosis	2.87	2.97	3.06	3.01	3.07	3.09	2.90	3.02	2.83	2.95	3.18	2.91
Unit root	-5.84	-4.96	-6.36	-5.54	-5.13	-4.11	-6.34	-2.02	-4.95	-3.56	-3.37	-4.68

Notes: The last row shows the Dickey-Fuller GLS statistics for unit root test (Elliott, Rothenberg and Stock, 1996). All the test statistics are statistically significant at the 1% significance level (except for SCS, which is statistically significant at the 5% significance level). Abbreviations of the industry names: Mining=MIN, Auto and Parts=A&P, Chemicals= CHEM, Electricity=ET, Construction and Materials=C&M, General Retailers=GR, Industrial Transportation=ITP, Software and Computer Services=SCS, Banks=BKS, Real Estate=RE, Health Care=HC, and Media=MD.

Table A2. Full-sample DY connectedness table.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD	FROM
MIN	19.89	7.41	9.04	7.87	8.70	7.51	9.03	4.77	6.06	7.06	7.23	5.43	80.11
A&P	7.00	17.32	8.93	8.44	7.36	7.79	8.75	5.51	5.76	6.81	8.96	7.38	82.68
CHEM	7.50	8.69	15.79	8.41	8.56	8.39	9.02	6.50	4.28	5.83	9.71	7.32	84.21
ET	6.42	7.92	7.79	18.64	8.90	7.40	10.43	4.79	6.20	5.98	8.10	7.42	81.36
C&M	7.20	7.34	8.65	9.04	17.79	7.78	10.45	5.32	5.23	7.16	8.15	5.88	82.21
GR	6.32	7.75	8.51	7.68	8.04	18.01	9.28	6.36	4.86	6.38	9.15	7.66	81.99
ITP	6.89	7.70	8.06	9.49	9.32	8.24	18.39	5.06	6.49	5.87	7.57	6.90	81.61
SCS	5.69	7.40	8.86	7.03	7.12	8.52	7.63	19.77	4.36	5.11	9.17	9.33	80.23
BKS	7.05	7.56	5.70	8.21	6.74	6.17	8.98	4.10	24.21	8.57	6.15	6.56	75.79
RE	7.30	7.59	6.76	7.39	8.40	7.42	7.64	4.43	7.30	21.70	7.25	6.82	78.30
HC	6.10	8.85	9.66	8.40	7.75	8.93	8.45	6.21	4.87	6.29	17.08	7.40	82.92
MD	4.90	7.81	7.56	8.14	5.81	8.15	8.09	7.47	4.96	6.27	7.86	22.96	77.04
TO	72.38	86.02	89.52	90.09	86.71	86.31	97.73	60.53	60.37	71.36	89.31	78.11	**80.70**

Notes: the upper-left 12-by-12 entries of the table report the pairwise directional connectedness among the industries. The last column shows the total directional connectedness FROM other industries to each of the industries. The last row shows the total directional connectedness from each of the industries to the other industries. The bottom-right element (in boldface) is the total connectedness.

Table A3. Full-sample short-term BK connectedness table.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD	FROM
MIN	7.99	2.02	2.76	2.06	2.40	2.00	2.33	1.35	1.39	1.44	1.70	1.31	20.77
A&P	1.67	6.99	2.77	2.01	2.22	2.01	2.25	1.59	1.20	1.45	2.33	1.46	20.96
CHEM	2.24	2.59	6.46	2.26	2.74	2.45	2.64	2.13	1.16	1.60	2.80	1.85	24.46
ET	1.68	1.90	2.32	6.33	2.22	1.81	2.44	1.30	1.17	1.24	2.03	1.25	19.35
C&M	2.12	2.24	2.98	2.40	6.85	2.40	2.79	1.77	1.45	2.07	2.40	1.55	24.16
GR	1.85	2.11	2.79	2.03	2.48	7.20	2.39	2.09	1.17	1.61	2.74	1.79	23.04
ITP	1.85	2.07	2.62	2.39	2.52	2.08	6.13	1.47	1.38	1.42	2.06	1.37	21.22
SCS	1.53	2.14	3.06	1.82	2.34	2.65	2.14	9.48	0.90	1.56	2.78	2.89	23.82
BKS	1.48	1.49	1.51	1.54	1.74	1.36	1.87	0.83	8.33	1.48	1.41	0.83	15.53
RE	1.45	1.70	1.99	1.51	2.38	1.77	1.79	1.33	1.41	7.97	1.66	1.20	18.18
HC	1.45	2.29	2.96	2.11	2.35	2.57	2.18	2.12	1.12	1.41	6.75	1.75	22.31
MD	1.32	1.70	2.31	1.53	1.80	1.97	1.73	2.50	0.80	1.22	2.03	7.60	18.90
TO	18.64	22.24	28.06	21.65	25.20	23.07	24.55	18.47	13.14	16.48	23.93	17.26	**21.06**

Notes: the upper-left 12-by-12 entries of the table report the pairwise directional connectedness among the industries. The last column shows the total directional connectedness FROM other industries to each of the industries. The last row shows the total directional connectedness from each of the industries to the other industries. The bottom-right element (in boldface) is the total connectedness.

Table A4. Full-sample medium-term BK connectedness table.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD	FROM
MIN	4.65	1.51	2.14	1.65	2.06	1.65	1.93	1.10	1.21	1.49	1.65	0.99	17.36
A&P	1.55	3.69	2.04	1.73	1.62	1.64	1.78	1.26	1.06	1.30	2.05	1.43	17.46
CHEM	1.70	1.89	3.73	1.82	1.99	1.87	1.89	1.57	0.75	1.11	2.32	1.50	18.40
ET	1.32	1.59	1.69	4.11	2.06	1.48	2.13	1.02	1.15	1.05	1.75	1.38	16.60
C&M	1.64	1.56	2.01	2.03	4.33	1.68	2.32	1.24	1.00	1.54	1.89	1.15	18.07
GR	1.34	1.66	1.98	1.57	1.86	4.16	1.97	1.52	0.86	1.26	2.14	1.56	17.72
ITP	1.51	1.58	1.77	1.98	2.20	1.77	4.08	1.11	1.26	1.06	1.64	1.30	17.18
SCS	1.28	1.56	2.09	1.47	1.64	1.92	1.57	4.76	0.84	0.88	2.22	1.97	17.45
BKS	1.33	1.34	1.07	1.46	1.33	1.06	1.64	0.82	5.16	1.51	1.10	1.02	13.68
RE	1.55	1.47	1.40	1.41	1.86	1.53	1.40	0.90	1.35	4.67	1.54	1.22	15.64
HC	1.34	1.95	2.32	1.76	1.77	1.96	1.77	1.38	0.86	1.23	3.94	1.42	17.76
MD	0.86	1.48	1.61	1.53	1.13	1.60	1.48	1.66	0.72	1.01	1.64	4.90	14.72
TO	15.43	17.58	20.12	18.40	19.52	18.17	19.86	13.58	11.06	13.44	19.95	14.93	**16.84**

Notes: the upper-left 12-by-12 entries of the table report the pairwise directional connectedness among the industries. The last column shows the total directional connectedness FROM other industries to each of the industries. The last row shows the total directional connectedness from each of the industries to the other industries. The bottom-right element (in boldface) is the total connectedness.

Table A5. Full-sample long-term BK connectedness table.

	MIN	A&P	CHEM	ET	C&M	GR	ITP	SCS	BKS	RE	HC	MD	FROM
MIN	5.05	2.57	2.84	2.74	2.90	2.58	3.17	1.57	2.24	2.71	2.61	1.99	27.90
A&P	2.50	4.46	2.79	3.07	2.35	2.73	3.08	1.78	2.22	2.61	3.06	2.88	29.07
CHEM	2.41	2.82	3.92	2.88	2.62	2.74	2.98	1.92	1.50	2.02	3.14	2.59	27.61
ET	2.24	2.89	2.53	5.51	3.12	2.68	3.86	1.63	2.47	2.34	2.87	3.06	29.67
C&M	2.33	2.36	2.51	3.09	4.65	2.48	3.61	1.57	1.79	2.34	2.62	2.05	26.76
GR	2.08	2.62	2.55	2.68	2.50	4.57	3.27	1.87	1.79	2.26	2.89	2.79	27.31
ITP	2.34	2.65	2.47	3.37	3.13	2.91	5.54	1.66	2.47	2.16	2.57	2.71	28.44
SCS	1.92	2.45	2.55	2.46	2.13	2.65	2.58	3.93	1.68	1.70	2.84	2.93	25.88
BKS	2.74	3.00	2.00	3.31	2.38	2.36	3.49	1.58	7.13	3.54	2.31	2.92	29.64
RE	2.84	2.86	2.22	2.86	2.77	2.68	2.85	1.43	2.90	6.07	2.66	2.77	28.84
HC	2.20	3.06	3.00	2.98	2.45	2.94	2.96	1.83	1.82	2.36	4.40	2.73	28.33
MD	1.71	2.97	2.39	3.25	1.85	2.97	3.12	2.20	2.11	2.52	2.73	6.93	27.83
TO	25.29	30.25	27.86	32.68	28.19	29.72	34.97	19.04	22.99	26.57	30.31	29.40	**28.10**

Notes: the upper-left 12-by-12 entries of the table report the pairwise directional connectedness among the industries. The last column shows the total directional connectedness FROM other industries to each of the industries. The last row shows the total directional connectedness from each of the industries to the other industries. The bottom-right element (in boldface) is the total connectedness.