Systemic risks and spillovers in the stock market of China: A sectoral analysis

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Abstract:
This paper investigates how risks spread across sectors of the stock market in China. Using graph theory and a recently developed time series technique, we are able to identify the most important sector in the market and the patterns of risk spillovers across sectors over time. Unlike the standard econometric modelling, the graph theory enables us to approach this question in a more reader-friendly way. Empirical results show that the industrial sector plays the most important role and should thus be considered a systemically important sector in the stock market of China. The spillover structure is found to be time-varying. While the industrial sector dominates the system for most of the time, other sectors, such as the consumer discretionary sector, also appear occasionally as the central sector. Our empirical results also indicate that the simple correlation based approach can produce equally useful information as the more advanced econometric models can.

Keywords: Contagion; Graph theory; Stock market; Spillover; Systemic risk

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1. Introduction

Financial markets have become remarkably volatile since the 2008 global financial crisis, which has attracted enormous attention from both academia and regulators to model systemic risk in financial markets and understand the patterns of how risks spread across markets or sectors. Systemic risk in financial markets threats "*the stability of or public confidence in the financial system*" (Billio et al., 2012) and impairs "*the functioning of a financial system*" (ECB, 2010). It is widely observed that since the 2008 crisis, systemic risk has shown clear contagious patterns, and risks have spread across countries, markets, sectors, and inevitably individual assets. Systemic risk contagion can cause considerably adverse effects on financial markets, domestic economy in a country, and more broadly the global economy. In this regard, understanding the mechanisms of risk contagion in financial markets is equally important, if not more, as modelling systemic risk *per se*.

Contagion, a widely discussed concept, has yet to gain a consensus on its definition (Sewraj et al., 2018). Dornbusch et al. (2000) suggest that contagion is "*best defined as a significant increase in cross-market linkages after a shock to an individual country (or group of countries)*". There are three key aspects of this definition: the interconnectedness of a market, spillovers of risks, and the source of the shock. In other words, shocks to one sector (or a group of sectors) can spillover to other sectors due to interconnectedness within a market, and thus cause significant (excessive) increase in the level of overall systemic risk. Following this logic, understanding risk contagion is thus conditional on mapping out the interconnectedness among sectors or markets, and identifying the mechanisms of risk spillovers as well as the source of shocks.

While the methods of mapping interconnectedness and spillovers have been well established in the literature (among many others, Diebold and Yılmaz, 2014, Acharya et al., 2017) and are kept being explored by researchers, identifying the source of contagion has been a topic attracting growing interest. For example, the Financial Stability Board (2010) introduced a concept called Systemically Important Financial Institutions (SIFIs), which is also discussed in Banulescu and Dumitrescu (2015). SIFIs are institutions that can cause significant disruptions to the wider financial system when they fail. The reasons why such institutions can cause systemic problems are potentially due to their large sizes and high level of connectedness within the financial system. Identifying these institutions are thus critical to both regulators and investors. SIFIs should be closely monitored and laid emphasis on in policy-making by regulators, as they contribute significantly to the systemic risk of the financial system. Investors, on the other hand, can also benefit from studying the behaviors of SIFIs and taking smarter trading strategies. Undoubtedly, the concept of SIFIs can be extended to non-financial institutions, sectors or markets.

With the fast development of China's economy over the last decade, China has risen to be one of the greatest contributors to the global economic growth. This trend is expected to remain for years. In China, the state controlled banking sector has played a dominant role in the financial system. However, since its establishment in 1991, China's stock market has been an increasingly important component in the financial system. It has acted as a necessary complement to the traditional banking sector, as it increases liquidity of equity capital, lowers firms' equity financing cost, and diversifies investors' portfolio choices.

Compared to most of the stock markets in developed countries, China's stock market has a relatively young history of less than 30 years. Despite being a young market, it has been developing rapidly and has become the second largest capital market in the world in terms of both trading volume and market capitalization. There are two exchanges, namely, Shanghai Stock Exchange and Shenzhen Stock Exchanges. Under the Shenzhen stock exchange there are also the SME (Small and Medium Enterprise) Board and ChiNext Board[1], respectively focusing on small and medium enterprises and innovative enterprises. There were totally 3,539 listed firms with a market capitalization of 53.94 trillion RMB (or 8.4 trillion USD) by the end of May 2018[2]. These listed firms can be broadly divided into eleven sectors.

Alongside its general success, Chinese stock market has often been considered a very risky investment arena, reflected by low returns and high volatilities (Su and Fleisher, 1998). Stock prices in China have frequently experienced booms and crashes since the very early stages of the market. The recent years, especially after the 2008 global financial crisis, have witnessed especially high volatilities in stock prices and more frequent and server market crashes. Another more recent and drastic one was the two major crashes and successive ones in the market from June to September 2015[3]. During

[1] The SME board under the Shenzhen Stock Exchange was launched in May 2004. As the first equity market for SMEs, there were 911 listed companies by the end of May 2018, with total market capitalization of 9.74 trillion CNY (about 1.5 trillion USD). The ChiNext board was launched in October 2009, mainly focusing on financing innovative enterprises, with total market capitalization of 5.066 trillion CNY (about 0.79 trillion USD) and 727 listed firms by the end of May 2018.

[2] Source: the websites of Shenzhen Stock Exchange (http://www.szse.cn/) and Shanghai Stock Exchange (http://www.sse.com.cn/).

[3] The Shanghai Composite index slumped from 5176 on 15 June 2015 to 2850 on 26 August 2015, and CSI 300

the massive crashes, for several times thousands of stocks hit the daily price-dropping limit within one trading day. The adverse effects of the crashes continued haunting the stock market for a long period afterwards. There were totally 16 times within the following seven months when thousands of stocks' prices plummeted by 10% (which is the daily price change limit) within one day.

After a massive market crash, it usually takes a long time for investors and the market to recover, causing long-lasting detrimental influences on both the stock market itself and the overall macro economy. Considering the significant importance of the stock market to long-run sustainable economic growth, it is crucial to maintain its efficient functioning and stability. One most effective way is to understand how systemic risks develop and evolve over time in the stock market, and more importantly, how risks spread across sectors. This paper will use sectors in the stock market of China as the unit of interest to study how risk contagion works in China markets, and aim to identify the systemically important sector(s) in the stock market.

In this paper, two approaches are adopted to investigate the risk contagion problem in sectoral returns of Chinese stock market. We start from a simple correlation based method and use the graph theory to visualize the centrality of the system and thus identify systemically important sectors (SISs). The second step is to use a rolling-windows approach to show how systemic risks have changed over time and whether the SISs have switched their positions within the system. The second method used is a recently developed time series approach proposed by Diebold and Yılmaz (2014) is

index from 5362 to 2952, with roughly 3.5 trillion USD market value evaporated.

then used to confirm our results from the correlation-based method, and to provide further information on the spillover effects across sectors.

Our empirical results from both methods present evidence that the Industrial sector has played the most important role in the risk transmission mechanism. Together with the Consumer discretionary and Materials sectors, they are three SISs in the Chinese stock market. These findings have much practical implications. Both regulators and investors should pay additional attention to these sectors' performance, and watch closely the movements and volatilities in these sectors, as they tend to lead the changes of market systemic risks and cause other sectors to follow their dynamics. Capturing the characteristics of volatilities and risk patterns in these sectors will help investors adjust their trading strategies in a timely fashion to avoid systemic risks, and at the policy-making level, assist authorities to identify the source of risk contagion and take ex ante measures to possibly prevent massive market failure/crash or alleviate its adverse effects.

In terms of methodologies adopted, it is worth noticing that the two methods eventually lead to consistent conclusions. The correlation-based method and graph theory may seem simpler to apply, and their results are easier to understand and interpret. In contrast, the time-series approach requires both the user and reader to have advanced background in econometrics, which may set up barriers to those without relevant foundation and deter them from well understanding the information conveyed. Through the lens of our research, we find that the empirical results from a simple correlation based method highly match those from the more complicated time-series method. Though the former is a relatively simple method and not technically challenging, it performs as well as the more advanced method, and provides equally reliable key information on risk contagion in China's stock market, but only in a more user-friendly fashion.

This paper contributes to extant literature in the following ways: First, it uses a simple correlation method to describe the interdependence in the sectoral network of China's stock market, which helps to precisely identify the leading sector(s), which plays critical roles in the mechanism of systemic risk contagion. On one hand, locating the source of risks solves one of the essential problems of curbing systemic risks from a regulator's perspective. On the other hand, knowing which sectors play the leading role and export risks to follower sectors is vital to investors to make sound trading strategies. Second, this paper adopts a VAR approach to account for systemic risk spillover effects, which provides solid evidence on identification of risk spillovers in a more formal way. Third, this paper is one of the scarce papers studying the sectoral correlation within China's stock market. Despite the increasing significance of China's economy and its financial market to both domestic and global economies, this area has been under-studied and is yet to explore. This paper fills in this gap by carefully examining the inter-sectoral connections and risk contagion mechanism within the stock market, hoping to aid and nourish potential users in the process of making policies or trading decisions.

The remainder of this paper is structured as follows: Section 2 reviews relevant literature with special focuses on the recent development of systemic modelling and methods for investigating contagion. Section 3 briefly introduces the methodology used in this empirical study. Section 4 describes the data with some preliminary statistical analysis. Section 5 reports and discusses the empirical results and the last section concludes.

2. Literature review

2.1Measuring systemic risks

The 2008 global financial crisis demonstrated how much systemic risks in the financial sector triggered by a tail event could propagate distinctly fast across markets and even countries. Systemic risk contagion is detrimental to a country's stock market and more broadly to the global economy. The profound impacts of the crisis on the international community have given rise to a booming literature of modelling and understanding systemic risk.

Research regarding quantitatively modeling systemic risk spillover has evolved fast in recent years. Benoit et al. (2017) and Silva et al. (2017), for example, respectively survey hundreds of relevant articles on this topic. New methodologies have emerged and extensive empirical work has been delivered. Albeit the fact this stream of research is growing fast, there are still "much remains to be done" (Benoit et al., 2017).

Given the focus of this paper, our discussion on the extant literature does not aim for a comprehensive review of all relevant topics. Instead, we focus particularly on recent discussions related to methodological issues and the stock market. Nevertheless, there are quite nice surveys on specific issues, such as De Bandt and Hartmann (2002) and De Bandt et al. (2012) on systemic risk in the banking sector; Glasserman and Young (2015) and Glasserman and Young (2016) on theoretical issues of systemic risk, from which interested readers can find very detailed information.

Techniques of identifying and measuring systemic risk have been well developed in the literature. Bisias et al. (2012), among several others, provide a survey on technical methods of studying system risk. The authors collect 31 quantitative methods from the existing literature[4]. The most relevant techniques to our study are network measures (Glasserman and Young, 2015, 2016). Rodríguez-Moreno and Peña (2013) compare a number of systemic risk measures using empirical data from the US and Europe, and suggest that the measure based on Credit Default Swap (CDS) spreads performs the best. Market-based data are easy to acquire and can provide real time evaluation, whereas accounting data generally come out with a delay and certain types of confidential data are not easily accessible to the public. This makes the method of using market-based information more appealing and popular.

Based on the well-known standard firm-level risk measures, namely, value-at risk (VaR) and expected shortfall (ES), Acharya et al. (2012) develop a model to measure systemic risk with systemic expected shortfall (SES). It also allows to calculate each individual's marginal contribution to systemic risk by its marginal expected shortfall (MES).

In this line of research, Acharya et al. (2012) and Brownlees and Engle (2017) introduce the SRISK measure, which is an extension of MES and allows to simultaneously consider the size and liabilities of each financial institution. Banulescu and Dumitrescu (2015) use the component ES approach to measure systemic risk. This method also allows them to identify the systemically important financial institutions without using

[4] The authors also developed an open-source Matlab code (http://www.treasury.gov/ofr) for most of the methods in their survey.

accounting data.

The CoVaR approach proposed by Adrian and Brunnermeier (2016) and modified by Girardi and Ergün (2013) adopts a conditional change in VaR in the financial system. Similarly, CoVaR measures the marginal contribution by a single financial institution to systemic risk or risk of other financial institutions. This approach has been largely used in empirical studies. For example. Reboredo and Ugolini (2015) compute CoVaR to detect changes in systemic risk in European sovereign debt markets after the Creek debt crisis. López-Espinosa et al. (2012) apply CoVaR to generate time-varying estimates of individual bank's contribution to systemic risk in an international large bank sample. Zhao et al. (2017) adopt the CoVaR model and document the risk spillover among the stock market, foreign exchange market and bond market in China from 2007 to 2017.

These market data based approaches generally requires the estimation of multivariate generalized autoregressive conditional heteroscedasticity (GARCH) model in advance. Copula and dynamic copula models have also been combined with these techniques to model dependence structure (for example, Reboredo and Ugolini, 2015, Oh and Patton, 2017) to model dependence structure.

Diebold and Yilmaz (2009), on the other hand, propose to use a vector-autoregressive (VAR) model instead. Their basic model is refined by Diebold and Yılmaz (2014) to set up a network analysis, which enables them to measure systemic risk and also risk spillovers at the same time. Risks from one market/sector can spread to another market/sector, causing chain effects or contagion. The idea of "excessive" spillovers is the core of contagion (Sewraj et al., 2018). It is sometimes hard to distinguish systemic risk measures and models for identify contagion as they tend to combine together, but for both investors and regulators, understanding risk contagion effects is also critical.

2.2 Testing contagion

The methods of testing contagion in financial markets can be divided in five categories according to Sewraj et al. (2018). They are conditional probabilities, correlation analysis, VAR based models, GARCH and copulas[5]. This paper will take two approaches, namely the simple correlation based analysis (for example, Støve et al., 2014) and a more formal VAR based model (Diebold and Yılmaz, 2014) to investigate risk contagion in Chinese stock market by looking at interconnectedness across sectors. With on-going reforms and growing global influences, the China's stock market has shown distinctive characteristics from those in developed countries. With its further integration into the global economy, China's stock market has been increasingly susceptible to global economic influences and international market shocks. There have been growing interest in this line of research. For example, Yao et al. (2018) confirm that financial liberalization in China has made its stock market more integrated with the global market. Shocks originated from the global market can exert important spillover effects on China's stock market, causing a rise in systemic risk and posting significant threats to its market stability (see for example, Mensi et al., 2016). Glick and Hutchison (2013) document that the equity market in China has had strong links with those in Asia since the global financial crisis, and the linkage has been increasing in recent years.

[5] See also Forbes and Rigobon (2001) and Forbes (2012) for relevant surveys.

From the opposite direction, Zhang (2017) shows that the contribution of Chinese stock market to global economy has increased substantially since the 2008 global financial crisis. Yu et al. (2017) also find evidence that risks in China's stock market have contributed significantly to other developed markets since the global financial crisis.

Although cross-country contagion effects of stock markets have been intensively studied, limited efforts have been seen in terms of investigating within-market risk spillovers in China (especially at the sectoral level), despite its growing importance to global financial stability and economic development. Among the sparse works, a most recent paper, Fang et al. (2018), uses the least absolute shrinkage and selection operator (LASSO) method on a selection of listed Chinese financial firms to study the network effect and risk transmission mechanism. Their empirical results identify an increasing network connectedness among firms, and show that individual firms' idiosyncratic risks are mainly driven by the risk spillover from other connected firms.

Lin and Sornette (2017) introduce the concept of speculative influence network (SIN) to look at sectoral causal relationship in Chinese stock market. Their study starts with a Hidden Markov Model (HMM) to allow for the market switching from a normal regime to a bubble state. Noticeably, their empirical work is essentially a special case applying to only the period between 2006 and 2008, when the Chinese market experienced a boom (bubble) and a subsequent market crash. Their sectoral analysis inspires us as an additional motivation to see how the sectoral network in Chinese stock market has evolved over time, and whether the shape of the network can be affected by methodologies applied.

3. Methodology

3.1 Graph theory

Correlation is one of the simplest ways to measure interdependence between variables within a network. Deeley (2016) demonstrates how to use graph theory to illustrate within-system dependencies via a simple mapping strategy. Denoting the correlation between two variables as ω_{ij}, the relationship between these two variables can then be defined by a simple distance function, i.e.:

$$f(\omega_{ij}) = \sqrt{2(1-\omega_{ij})} \qquad (1)$$

Using function (1) to calculate pairwise distances in the system and then connecting all variables in an undirected network graph G, a minimum spanning tree (MST) (Mantegna and Stanley, 2000) can be found to connect all variables (nodes) with the minimum possible total edge weight. In this paper, the MST problem is solved by the Kruskal's algorithm, which can be found in Cormen et al. (2001).

After illustrating the minimum spanning tree, the centrality in the network can be measured by three indicators, namely, incidence, closeness and betweenness, to identify the most central variable(s) in a network. The first measure incidence is defined as the total number of edges incident/connected to a node. In brief, it shows how many ties a node has. The more ties a node has, the more central it is in the system.

The second measure closeness is defined as the reciprocal of the farness between a node i and all other nodes in the graph, calculated by $c_i = 1/\sum_{j=1}^{n} f(\omega_{ij})$, for $j \neq i$, whereas n is the total number of nodes (Bavelas, 1950, Sabidussi, 1966). Higher closeness of a variable indicates shorter distances from that node to all others nodes, thus making this node more central in the graph. Finally, betweenness measures how often a node appears as a linking bridge along the shortest path between two other nodes. It provides an alternative measure of centrality. The more central the node is, the higher probability it occurs as a bridge on the shortest path between two other nodes.

3.2 VAR based method

These centrality measures in graph theory basically answer the question of which node(s) is characterized as most central within a network. It is tempting to think that a most central variable (node) should also be the most important one in a system. It is, however, too quick to jump to this conclusion, as being central does not necessarily guarantee being the most influential (though in many cases this conclusion may seem to hold). It is necessary to dig deeper and rely on more formal econometric tools to identify the most important contributor in the system, rather than based only on correlations.

Recently, a growing body of literature (for example, Zhang et al., 2018) has used the Diebold and Yılmaz (2014) approach for the measure of systemic risks. It is based on the vector autoregressive (VAR) model and the generalized forecast error variance decomposition method (GFEVD) (Koop et al., 1996, Pesaran and Shin, 1998). The results of variance decomposition tend to vary with different setups of the model (ie. difference in ordering of variables). We therefore use the generalized decomposition method to resolve the issue of ordering in standard VAR analysis.

Given no prior information on the underlying series of a system, all of the variables should be considered endogenous and be estimated in a VAR model (Sims, 1980). Upon estimating the model, the FEVD approach can then be used to find out how much one variable (*i*) can help in explaining the variation of another variable (*j*). Denote the FEVD of any two variables as φ_{ij}, which gives how much variable i is explained by variable j, then an $\mathrm{n} \times \mathrm{n}$ connectedness matrix (i.e. Zhang, 2017) can be constructed for all pairs of variables in the n-variable system. For any pair of variables (i, j), the relative contribution can be calculated as $\varphi_{ij} - \varphi_{ji}$. A positive value means variable j contributes more to variable i than variable i contributes to variable j. In other words, variable j is a net contributor to variable i. The top net contributor in a system should be the one who is most influential among all variables, and thus can be validated as the most important variable in the system.

This approach explores the explanatory power of one variable to all other variables within a system. Ideally, when a variable i can explain largely the variations in all other variables in the system, this variable's movements can be used to predict the subsequent movements of others'. This can be viewed as a co-movement led by variable i and followed by all others. Identifying this variable is crucial, as it acts as the source of whatever is transmitting through the system (for example, information, risks). It is thus possible to address spillover effects across the whole system based on this approach, as risks can be considered to spread sequentially from the biggest to the least contributors within the system.

In the connectedness matrix, the total value is n. While the diagonal elements show self-contribution ($\mathrm{i} = \mathrm{j}$), the aggregation of all off-diagonal elements shows how much the system is connected. Based on this, Diebold and Yılmaz (2014) define a measure of systemic risks as:

$$s = \frac{1}{n}\sum_{j=1}^{n}\sum_{i=1}^{n}\varphi_{ij}\,, for, i \neq j \qquad (2)$$

They also introduce three additional measures:

$$\mathrm{fs}_i = \sum_{j=1}^{n}\varphi_{ij}\,, for, i \neq j \qquad (3)$$

$$\mathrm{ts}_i = \sum_{j=1}^{n}\varphi_{ji}\,, for, i \neq j \qquad (4)$$

$$\mathrm{ns}_i = \mathrm{ts}_i - \mathrm{fs}_i \qquad (5)$$

where fs_i describes how much one variable gains from the system; ts_i describes how much it contributes to the system; ns_i calculates this variable's net contribution to the system, which can be positive or negative.

4. Data

The data of sectoral returns in China's stock market are collected from Wind Financial database from 7 January 2000 to 10 May 2018. The data we use in this paper are in weekly frequency and thus contain totally 926 observations. Using weekly return data can help to reduce higher frequency noise, while maintain the dynamic dependency structures in the market. According to the Wind Financial database, there are 11 sectors in the stock market of China. Sector definitions and notations are given in Table 1.

(Insert Table 1 here)

Descriptive statistics of weekly returns in each sector are reported in Table 2. Among all sectors, the Health care sector has the highest average returns, whereas the Energy sector performs the worst. The Telecommunication sector is the riskiest sector of all with the highest standard deviation, while the Utilities sector has the lowest standard deviation. Almost all sectors (except Energy, Financial and Telcom sectors) have negative skewness, and all return series exhibit extra Kurtosis and do not have normal distribution.

(Insert Table 2 here)

The first step of a preliminary analysis is to construct a correlation matrix and see how these sectors are correlated to each other. Figure 1 uses a heat map to visualize the sectoral interdependences.

(Insert Figure 1 here)

For any correlations that is above 0.8, it is marked in red (except diagonal elements). It can be spotted that among all sectors, the Telecommunication sector has the coldest color (reflecting a lowest aggregated correlation with all other sectors). The maximum correlation is 0.61 for this sector, which is with the Industrial sector. In comparison, much warmer colors (meaning higher correlations) are seen for Materials, Industrial and Consumer discretionary sectors.

5. Empirical results

5.1 Results based on graph theory

Given the correlation matrix, we can calculate the distance between any two variables and then find out the minimum spanning tree for the system. Figure 2 shows the MST results:

(Insert Figure 2 here)

As shown in the MST, the Industrial sector is marked red as it is the center and connects the most nodes. To provide further evidence that the Industrial sector plays a central role, Figure 3 plots the rankings of three centrality measures. The left panel shows the rankings of sectors according to node incidence (or the number of nodes connected); the right panel shows rankings based on node closeness (the upper right panel) and node betweenness (the bottom-right panel). All three centrality measures convey consistent information, and indicate that the Industrial sector is the most central, leading sector in the stock market of China.

(Insert Figure 3 here)

It should be noticed that correlations among sectors are not necessarily time-invariant, especially in our sample which covers a period of more than 18 years. During this relatively long period, the stock market in China experienced several major crises. One would reasonably expect that the correlation structure of the system has changed over time and the most important sector should also have switched. To address this possibility, we perform a rolling-windows analysis. Using 100 window size and the same MST centrality analysis discussed above, Figure 4 plots the rolling central sector distributions. The figure clearly shows that the systemically most important sector did change over time. While the Industrial sector kept its central role in most of the windows (61.1%), the Consumer discretionary (25.6%) and Materials (13.3%) sectors occasionally took the leading role. Noticeably, the Consumer discretionary took the central position mainly before the 2008 global financial crisis (there was also a market crash in China in 2008) for a roughly three-year period. The Materials sector became more important between 2015 and 2017, when the international commodity markets was experiencing higher risks (Al-Maadid et al., 2017).

(Insert Figure 4 here)

Following Deeley (2016), we use the hidden Markov models (such as Staum et al., 2016) to study time-varying systemic risks in the system. Assuming that there are three latent states, respectively corresponding to the low, medium and high levels of risk contagion, Figure 5 depicts how systemic risks have changed across these three states over time. It is clearly observable that there are four major periods featured with high probability of high-risk states, where the probabilities of having highly correlated pairs are much higher, implying higher level of risks.

(Insert Figure 5 here)

It is interesting to notice that none of the high systemic risk states actually happened during the 2008 global financial crisis period. Two high-risk states had appeared before the 2008 crisis, around the year 2001-2002 and 2005 respectively, whereas the other two major risks arose in 2009 and 2016.

5.2 Results based on VAR

As mentioned above, the correlation analysis indeed provides some interesting results. It is yet to draw a conclusion because there is no formal econometric/regression analysis. To further confirm the results from the correlation analysis, we proceed to employ a standard econometric method on the data. We use the approach proposed by Diebold and Yılmaz (2014) to study sectoral connections in the stock market of China.

First, the full sample for all 11 sectors is fitted into a VAR model and the GFEVD method is used to get the connectedness matrix (shown in Table 3). The overall connectedness (s) is 85.13%, indicating that the sectors within the system are highly connected. In other words, the systemic risk in the stock market is high in China. Seen in the figure, the column "from" shows that all sectors gain quite substantial information from the system (ranging from 75.33% to 87.91%, with most sectors around 85%). Their contributions to the system, however, vary significantly. Shown in the row "To", the top contributor in the system is the Industrial sector with a total contribution of 105.70%, whereas the lowest is the Telecommunication sector contributing only 41.77%. The Telecommunication sector also receives least from the system among all sectors. It should be noticed that there is an upper bound for the measure "From" (100% maximum variation for any variable), whereas the measure "To" can exceed 100% (in theory, it can go to a maximum value of n).

(Insert Table 3 here)

Other than the aggregated measures of "from" (contributing) and "To" (receiving) for each sector, it may also be more informative to look at the net measure and compare it to the centrality results. The net contributions for each sector are shown in the last row "Net" in Table 3 and are also plotted in Figure 6. The top three net contributors to the system are the Industrial, Consumer discretionary, and Materials sectors, each with over 10% net contribution to the system. The Telecommunication sector receives the most from the system, with a negative net contribution equaling -33.58%. These results are consistent with those of the simple correlation method using graph theory.

(Insert Figure 6 here)

Figure 7 plots pairwise connectedness based on the relative contribution of each pair in the system. With 11 sectors in total, there are 55 edges connecting 11 nodes in the figure. In this system, if variable i explains more than it is explained by variable j ($i \neq j$), then an outward edge (arrow) is drawn pointing from i towards j to show the net directional connectedness, or otherwise an inward edge. In Figure 7, the number of outward edges for each sector is showed in their labels. Doing so allows us to obtain a general view of how each sector interacts with others. It can be easily identified which sector contributes the most and which one the least, by comparing their numbers. Larger numbers are also set to appear in bigger font sizes and darker colors. When the number of outward edges becomes smaller, the font size is set to shrink and the color becomes lighter. As the number indicates how many outwards edges this sector has, a bigger number thus means that more net contributions are made by this sector to the system. Among all sectors, the Industrial sector ranked the first in this system with totally ten outgoing edges, representing it is contributing to rather than receiving from the rest sectors in the system. As the net contributor to all other sectors, the Industrial sector should be considered the systemically most important sector in this system. Following the Industrial sector, the second most important one is the Consumer discretionary sector with nine outward edges and then the Materials sector with eight, which is in the third position. The Telecommunication sector has zero outward edge, meaning it is a net receiver affected by all other sectors but contributes to none. This is consistent with what we have found in the total net directional connectedness in the connectedness matrix, where the Telecommunication sector is found to have the largest net gain (33.58%) from the system.

(Insert Figure 7 here)

Again, the rolling windows approach is applied and the VAR model is estimated for each window. A rolling version of connectedness is plotted in Figure 8, which shows the dynamics and depicts a time-varying picture of how systemic connectedness has evolved over time. There are roughly four high-risk periods, which are reasonably consistent with those shown in Figure 5. The early stage of high systemic risk from 2002 to 2004 fell in 2005 and rose again after the global financial crisis in 2008. Two additional high-risk periods can be seen around 2013 and 2016, corresponding to the periods when most of the sectors had high correlations (Figure 5).

(Insert Figure 8 here)

It is also worth examining the ranks of sectors under the rolling-windows setup. Figure 9 plots the two sectors contributing the most to the system, the Industrial sector and the Consumer discretionary sector. Although there are some variations over time, these two sectors almost always rank on the top. The Industrial sector contributes the most to the system in almost all rolling windows, whereas the Consumer discretionary sector occasionally takes over the top contributor's position.

(Insert Figure 9 here)

6. Conclusions

This paper investigates the issue of systemic risk measures and contagions across sectors in the stock market of China. Under the backdrop of global financial crises and increasing interactions among regional economies and financial markets, systemic risks and their contagion have been studied by a growing body of literature, proposing various methods of measuring systemic risks and studying the patterns of risk spillovers. Rather than modeling systemic risks and take ex post measures when market crashes, we argue that it is at least as important to understand the mechanism of risk contagion and pinpoint the source of contagion, in order to take ex ante measures before the systemic risks spread and contaminate the whole system.

Among other methods trying to map within-system connectedness and spillovers, this paper tries to identify systematically important sectors (SISs) who lead the risk flows in the stock market. Using simple correlation as a measure of interdependency between sectors and the graph theory, namely, the minimum spanning tree approach, we are able to show that the top central sector (SIS) in the system is the Industrial sector. It is followed by the Consumer discretionary sector and Materials sector as the second and third most central sectors. To account for possible dynamics of their position switching, a rolling windows examination is adopted and shows that their relative positions in the stock market have indeed switched over time. Notwithstanding, the Industrial sector keeps its top position in the majority of the windows (61.1%), while on few occasions the Consumer discretionary or Material sector take the top position.

To confirm that the most central industries play a systemically most important role in the stock market and lead other sectors to co-move, we then use a recently developed time series model and compare the results with the findings of the foregoing correlation based analysis. The Diebold and Yılmaz (2014) approach is applied to these sectoral returns to show the time-varying systemic risks. This approach enables us to examine how the system interacts and behaves over time. Interestingly, both methods produce consistent results in the time-varying systemic risks and also risk spillover patterns. The Industrial sector is confirmed by both methods to be the central and systemically most important sector in China's stock market. Its risks and changes contribute the most to the system and lead the dynamics of the whole market.

Our empirical results have clear implications to both practitioners and authorities. First, it is strategically important for the investors to understand how risks spread across sectors and identify which sector is the leading sector and others will be following its patterns. The performance of the systematically important sector can generate useful signals to the investors, so that they can accordingly rebalance their portfolio choices against systemic risks. On the other hand, identifying the sectoral positions in the stock market and their roles in risk contagion also has important meanings to the authorities in monitoring risks and avoiding overall market crashes. Finding the systemically most important sector(s) is critical for policy interventions when facing high level of systemic risks and potential market crashes.

Through the lens of our research, it is interesting to find that the correlation based method and the more complicated time-series econometrics model finally reach a consensus in terms of identifying the leading contributor(s) in the risk contagion mechanism. The correlation based analysis and graph theory may seem technically straightforward and simple, but they manage to produce almost the same results as the more complicated time-series model does, and both methods lead to consistent conclusions. From a user-friendly perspective, we argue that as the correlation based model is relatively easier to apply and understand even by those who have no advanced econometric background, it should have much more potentials in practice without losing key information or compromising the quality of findings.

Going hand in hand with the fast development of China’s stock market and its increasing interactions with the international market is the growing susceptibility to risks from various sources, not only domestic but also international. Previous studies have rarely discuss the issues concerning risk contagions in China’s stock market. This paper fills the gap in this regard by carefully examining the interrelationships among sectors in this market and discover its risk spillover mechanism. On the other hand, the much more frequent exposures to systemic risks and increased proneness to market crashes have been constantly alerting both investors and policy-makers to take proper actions. It is fundamentally important to understand how systemic risks spread across the market. Our research hopes to serve as a useful tool to aid them in identifying the risks and curbing the spillover effects of systemic risks.

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Tables and Figures

Table 1. Sector definition and notations

Notation	Sectors	Details
Energy	Energy	Energy equipment, service, oil, gas and other fuels
Materials	Materials	Chemicals, construction materials, containers and packaging, metal, mining and other materials
Industrial	Industrial	Aviation and defense, construction, electronics, infrastructure
Con. discret	Consumer discretionary	Car and parts, durable consumption, hotel, restaurants and others
Con. staples	Consumer staples	Food and beverage, and other retail products
Healthcare	Health care	Medical, health care, equipment and biotechnology
Financial	Financial	Banks, insurance, capital market, real estate
IT	Information Techonology	Software, services, technological hardware
Telcom	Telecommunication services	Telecommunication service and products
Utilities	Utilities	Electricity, gas, water and other utilities
Estate	Real estate	Real estate index

Note: sectoral definition is given by Wind Finance Database.

Table 2. Descriptive statistics

	Mean	Median	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Energy	0.184	0.068	4.018	0.056	5.482	238.155***
Materials	0.240	0.282	4.258	-0.284	5.500	253.528***
Industrial	0.229	0.267	4.085	-0.251	6.080	375.727***
Con. discret	0.267	0.331	4.068	-0.222	5.630	274.576***
Con. staples	0.285	0.360	3.812	-0.091	5.124	175.342***
Healthcare	0.330	0.333	3.964	-0.178	5.149	183.041***
Financial	0.236	0.086	4.051	0.313	5.353	228.7568**
IT	0.251	0.230	4.655	-0.273	5.068	176.559***
Telcom	0.254	0.011	5.274	1.325	14.286	5185.094***
Utilities	0.193	0.183	3.666	-0.407	7.136	685.674***
Estate	0.260	0.218	4.717	-0.019	5.120	173.488***

Note: *** denotes 1% level of significance. Series are weekly growth rate (%).

Table 3. Diebold and Yilmaz (2014) connectedness matrix

	Energy	Materials	Industrial	Con. discret	Con. staples	Healthcare	Financial	IT	Telcom	Utilities	Estate	From
Energy	15.60%	11.07%	10.20%	9.07%	7.85%	6.82%	9.26%	6.94%	4.69%	9.72%	8.78%	84.40%
Materials	8.80%	12.44%	11.30%	10.86%	9.14%	8.98%	6.98%	9.27%	4.03%	9.73%	8.48%	87.56%
Industrial	7.85%	10.94%	12.09%	11.08%	9.31%	9.34%	6.82%	9.87%	4.36%	9.87%	8.47%	87.91%
Con. discret	7.11%	10.69%	11.27%	12.23%	9.92%	10.13%	6.53%	10.44%	3.97%	9.38%	8.34%	87.77%
Con. staples	6.97%	10.20%	10.76%	11.27%	13.83%	10.97%	6.23%	9.82%	3.56%	8.64%	7.74%	86.17%
Healthcare	6.13%	10.15%	10.93%	11.65%	11.14%	14.06%	5.15%	11.11%	3.49%	9.14%	7.03%	85.94%
Financial	9.90%	9.36%	9.45%	8.88%	7.47%	6.09%	16.78%	6.18%	4.52%	8.82%	12.55%	83.22%
IT	6.17%	10.28%	11.30%	11.77%	9.73%	10.86%	5.18%	13.87%	4.63%	8.84%	7.37%	86.13%
Telcom	7.49%	8.06%	9.01%	8.10%	6.36%	6.14%	6.75%	8.42%	24.65%	8.15%	6.86%	75.35%
Utilities	8.49%	10.66%	11.17%	10.41%	8.48%	8.84%	7.17%	8.72%	4.45%	13.53%	8.09%	86.47%
Estate	8.19%	9.98%	10.30%	9.98%	8.15%	7.34%	10.87%	7.86%	4.08%	8.73%	14.52%	85.48%
To	77.09%	101.39%	105.70%	103.09%	87.56%	85.50%	70.94%	88.62%	41.77%	91.03%	83.72%	
Net	-7.31%	13.83%	17.78%	15.32%	1.39%	-0.44%	-12.28%	2.49%	-33.58%	4.56%	-1.76%	

Note: From (fs_i) is the horizontal aggregation of each variable in the matrix (excluding diagonal elements); To (ts_i) is the vertical aggregation of each variable in the matrix (excluding diagonal elements); whereas Net (ns_i) is the difference between To and From.

Table 4. Summary of rolling-windows estimation

		Energy	Materials	Industrial	Con. discret	Con. staples	Healthcare	Financial	IT	Telcom	Utilities	Estate
To	Mean	76.98%	100.46%	103.89%	102.04%	84.93%	84.75%	73.83%	86.68%	49.19%	88.48%	83.25%
	Std. Dev.	7.90%	4.24%	4.95%	3.75%	10.52%	10.19%	14.38%	6.95%	16.61%	5.62%	7.86%
From	Mean	84.20%	87.57%	87.92%	87.79%	85.54%	85.50%	83.10%	85.97%	75.33%	86.25%	85.32%
	Std. Dev.	3.45%	1.52%	1.31%	1.42%	3.46%	3.38%	4.73%	2.63%	11.40%	2.04%	3.27%
Net	Mean	-7.22%	12.90%	15.97%	14.24%	-0.60%	-0.74%	-9.27%	0.70%	-26.14%	2.23%	-2.07%
	Std. Dev.	5.47%	5.31%	6.09%	4.96%	7.32%	7.23%	10.24%	5.11%	8.49%	5.43%	4.94%

Note: Window size is set to be 100 observations. From (fs_i) is the horizontal aggregation of each variable in the matrix (excluding diagonal elements); To (ts_i) is the vertical aggregation of each variable in the matrix (excluding diagonal elements); whereas Net (ns_i) is the difference between To and From.

Figure 1. Correlation structure in a heat map

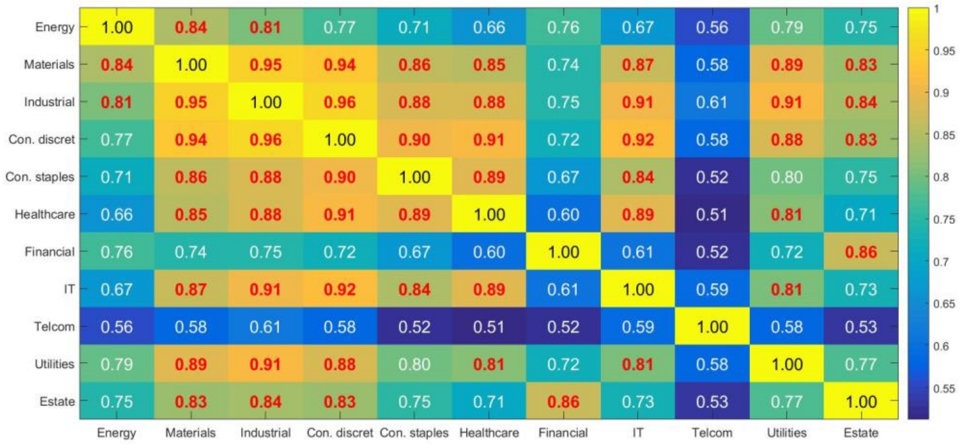

Figure 2. Minimum spanning tree (MST) for correlation distance

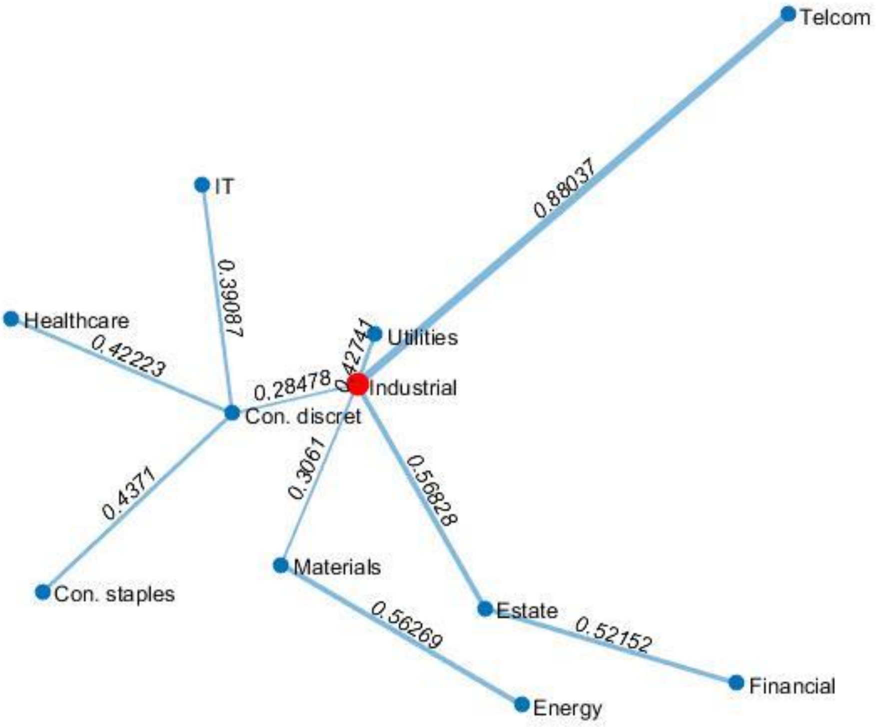

Figure 3. Sector centrality measures based on MST

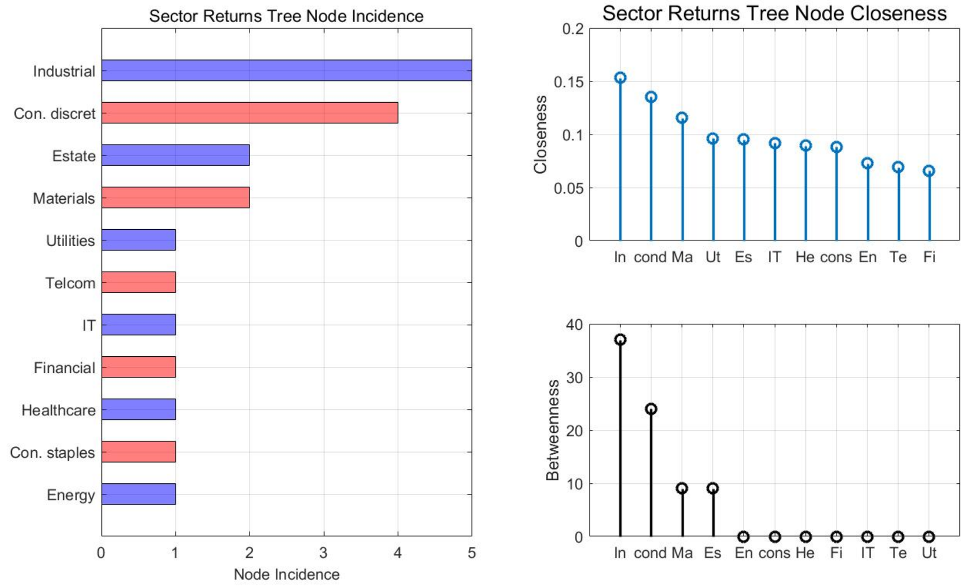

Figure 4. Central sector distribution over the rolling windows (win=100)

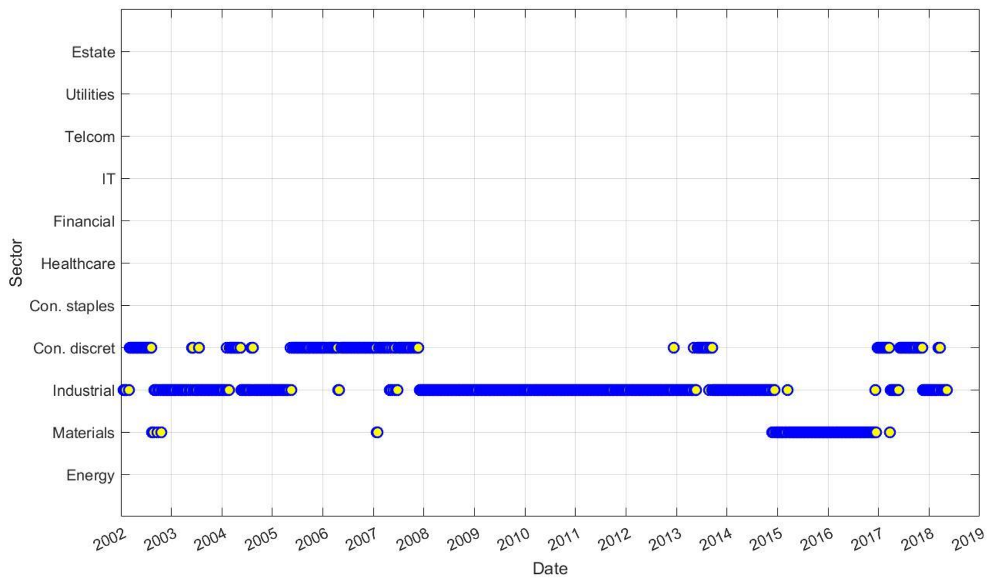

Figure 5. Three-state hidden Markov chain

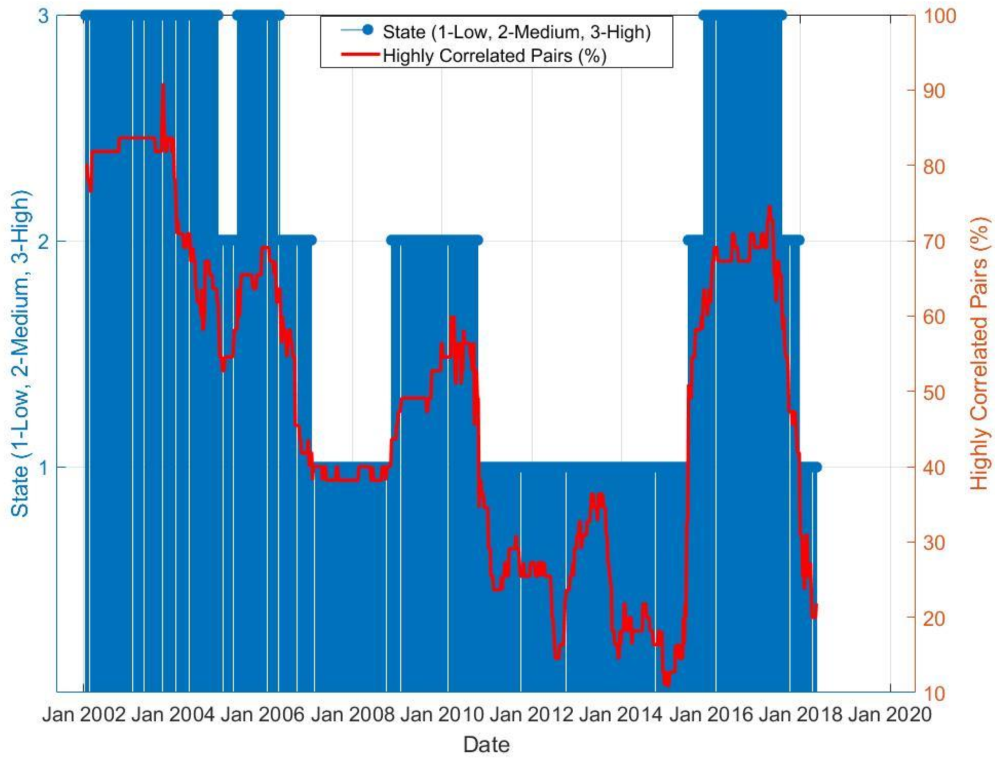

Figure 6. Net contribution to the system

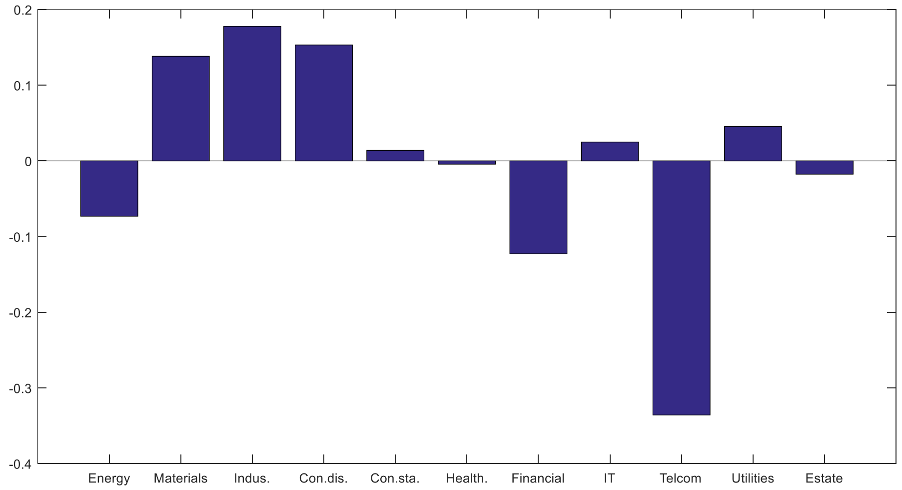

Figure 7. Pairwise net connectedness plot of the full sample (Note: the number in the label shows how many outward edges are from that sector)

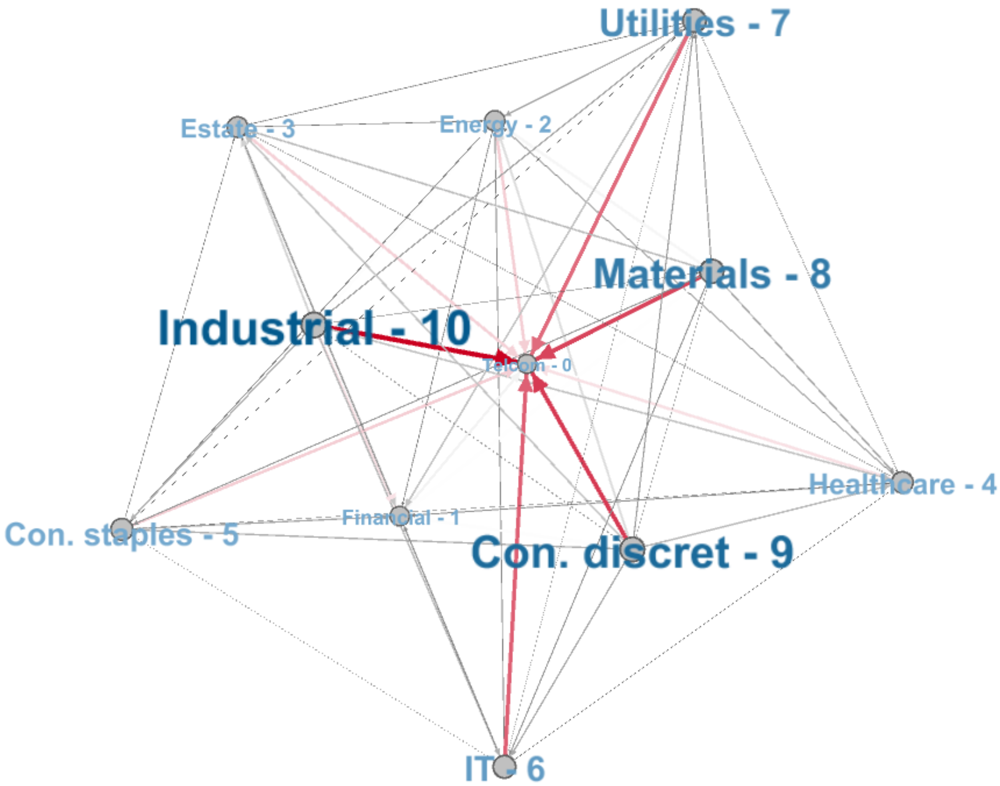

Figure 8. Rolling windows connectedness measure

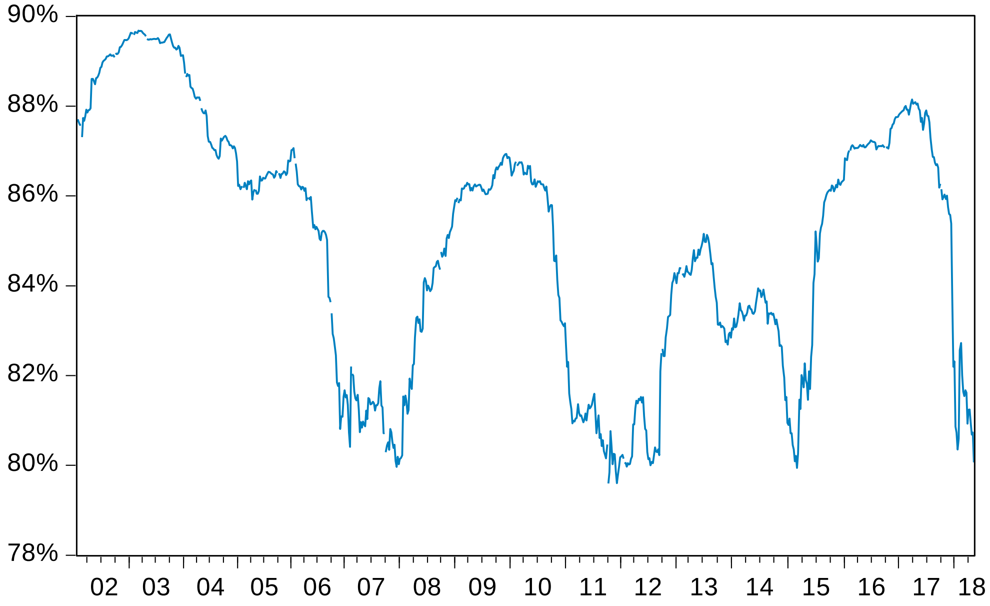

Figure 9. Rolling windows contribution to the system by the top two sectors