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Risk Transmission Mechanism across Industries in China

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Abstract

Learning how the financial risk has been transmitted between industries in China before and after some big events is a crucial topic in risk management. Due to the large number of industries in China, the market can be regarded as a high-dimension network. To conduct the empirical research on risk transmission mechanism in China based on daily data of the SWS (Shen Wan Security) secondary industry index, I utilize the LASSO algorithm to compress, select and estimate variables and build a high dimensional VAR model and calculate the pairwise risk connectedness between different industries. With the help of network analysis, I visualize the outcome of the VAR-Lasso model. Then, both full sample estimation and rolling window estimation are applied to provide static analysis and dynamic analysis on the risk transmission network. Based on the analysis, clustering characteristics can be easily found in risk transmission of the market, especially between industries in the same industrial chain or between industries that are closely connected. Particularly, Oil exploitation, Insurance, Banking, and

Railway Transportation are functioning as an efficient intermediary nodes in the whole transmission process. As for dynamic analysis, the overall risk connectedness reaches the summit during the great stock crisis in 2015 and the shock of COVID-19. Comparisons are made on the risk transmission network before and after those big events.

1 Introduction

Financial risk is a form of danger that can cause interested parties to lose money. Various macroeconomic factors, fluctuations in the market interest rate, and the threat of default by industries or large companies all put financial markets at risk. Financial risks have received more focus since the financial crises in 2008. On the one hand, in the context of globalization and financial liberalization, the individual risk of financial institutions can be better identified and controlled under the framework of the Basel Agreement[1], but the risk spillover effect among financial institutions still exists. Once the risk among financial institutions reaches a certain threshold, the market will be subject to an unavoidable negative impact; and the current supervision of that type of risk among financial institutions is still unavailable, which indicates the lack of risk management under the current financial regulatory system. The absence of risk management also shows that micro-prudential policies cannot effectively prevent risk contagion among finan-

[1]Basel Agreement is also called Basel Accord. The Basel Committee on Bank Supervision established the Basel Accords, which are a collection of three banking regulation agreements (Basel I, II, and III) (BCBS). The Committee makes recommendations on banking and financial legislation, focusing on capital risk, market risk, and operational risk in particular. The agreements ensure that financial institutions have sufficient liquidity on hand to cover unforeseen losses.

cial institutions and the financial crises will be triggered. On the other hand, in recent years, the rapid development of financial technology based on mobile Internet, artificial intelligence, big data, cloud computing, blockchain has expanded the boundaries of financial services, improved financial service efficiency, and formed a series of new financial service model based on the technological innovation. However, financial risks related to the innovation also occur, such as technical security vulnerabilities, online fraud risks, data security and privacy protection, and the use of the Internet to engage in illegal financial activities. Fintech has not only brought energy and power to the financial system but led to more shocks to the system. Stock market can reflect the status of most of the industries (primary industry, secondary industry and tertiary sector) in the country. Thus, many people are interested in how the risk is developed and transmitted among industries in the stock market. With the development of a mixed operation in the market, the connectedness between each sub-industry in the market has risen to a high level, which can be interpreted as a complex network. The spillover effect, which is introduced by Cheung & Ping (2004), has been widely spread by the network. According to the definition of Cheung & Ping (2004), spillover effect refers to the impact that seemingly unrelated events in one nation can have on the economies of other nations. Although there are positive spillover effects, the term is most commonly applied to the negative impact a domestic event has on other parts of the world such as an earthquake, stock market crises, or another macro event. The spillover effect is a special characteristic of the network formed by financial institutions. The main reason for the increase in the spillover effect is the globalization in trade and tight connections between financial units. For example, the US-Canada trade relationship can generate spillover effects as the US is the main market of the business of Canada. Moreover, China has become a major source of spillover effect since 2009 due to the development of Chinese manufacturers. Worldwide trade can likely be negatively influenced when the Chinese economy experiences a downturn, according to Findlay & O'rourke (2009).

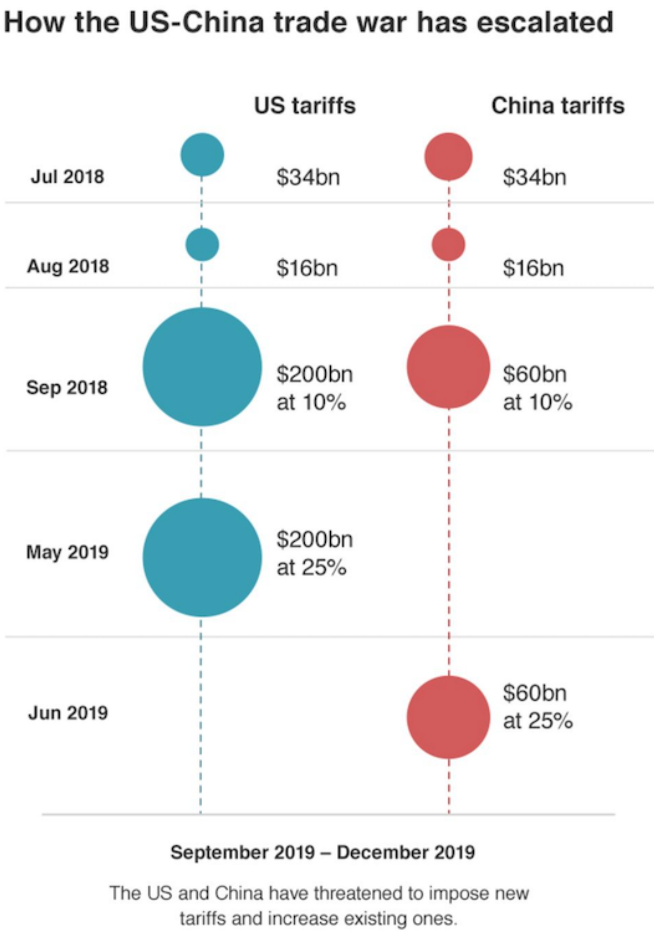

Figure 1: Trade War between China and US from Ahelegbey & Giudici (2020)

Once the spillover effects become a global effect, the system risk will rise and Diebold & Yilmaz (2012) says the units in the system are connected under risk, which is risk connectedness. Risk connectedness is the central concept to risk management and risk management is a management process that includes the definition, measurement, evaluation and development of strategies to respond to risks. The goal is to minimize the avoidable risks, costs and losses. Ideal risk management, with prioritized priorities, can give priority to events that cause the greatest loss and the highest probability of occurrence, and then deal with events with relatively low risks. With the development of the global market, new competitive situations and cooperative relationships have emerged among different fields. For example, the trade war between China and the US, which is shown in Figure 1, has exerted a deep influence on many industries. According to Figure 1, the trade war originated from the US President Donald Trump's declaration on March 22, 2018 when he signed a memorandum that "China steals US intellectual property and trade secrets" and required the US Trade Representative to deal with the slaves. The US government imposes tariffs on imports from China, involving a bunch of goods worth 60 billion dollars, and sets other trade barriers to force China to change its "unfair trade practices." The United States alleges that these actions have led to the expansion of the trade deficit and forcing the transfer of technology to China. On July 6, 2018, the United States imposed an additional 25% tariff on U$34 billion worth of Chinese exports to the United States. Chinese Ministry of Commerce took countermeasures on the same day, imposing an additional 25% tariff on $34 billion worth of U.S. exports to China, including soybeans, the most exported product from the United States to China. Based on the study of Liu & Woo (2018), the trade war has hurt the economy of both the United States and China. In the United States, consumers have to face higher prices, and agricultural producers and manufacturing producers are also facing financial difficulties. In China, the annual growth rate of gross national product (GDP) has fallen to the lowest level in recent decades. The economies of other countries are not immune, even if a small number of countries benefit from filling the gap in demand for affordable production. The trade war also caused turbulence in the stock market. Governments of various countries have introduced new measures for the damage caused by economic friction.

Another event that can lead to large risk connectedness is the COVID-19. The COVID-19 was first discovered in Wuhan in 2019, and was officially declared as a "global pandemic" by the World Health Organization (WHO) on March 11, 2020. According to data released by the National Bureau of Statistics of China on March 16, Chinese output growth of industries, investment, and consumption fell by 13.5%, 24.5%, and 20.5%, respectively, and the unemployment rate reached 6.2% from January to February. The outbreak of the epidemic has had a major impact on the safety of human life and the development of the Chinese economy. Chinese companies also face huge challenges in the prevention and control of the epidemic. Due to the need for epidemic prevention and control, the production and operation activities of enterprises are restricted, and short-term operations are under huge risks. Based on the research of Ahelegbey & Giudici (2020), due to the specialization of the market and division of labor between industries, the dependence among industries has gradually been strengthened. In the recent epidemic around the world - COVID-2019Huang et al. (2020), risk spread rapidly from the basic industries including traffic, medicine, and agriculture to the whole market, which demonstrates that a local market can become the source of risks as long as it is affected by risk factors and risks be linked to other industries through pipelines such as logistics, capital flow, and information flow. Plus, to contain the epidemic, quarantine has been widely adopted around the world so some economies have been temporarily shut down, and financial markets have also come into a state of continuous recession. Many stock indexes have a huge decline between February and March, which indicates that those stock markets should have been connected within a network.

The mechanism behind the risk transmission process is complicated, which covers numerous industries and countries. There are two approaches that risk connectedness follows to influence the world: i) the friction among two or more countries, which originates from many aspects of the country; ii) the shock to a specific field and the impact will be spread soon to other fields. For the first approach, the trade war is a good example to follow and the COVID-19 in China can explain the second approach. Thus, policymakers can make more optimal decisions to handle the risk as long as they can figure out the risk transmission mechanism. Also, companies in certain fields can effectively avoid risk once they know the mechanism. However, the whole market is a big network that involves many nodes and edges. There is, however, little empirical research on Chinese market risk connectedness. This is particularly unfortunate given the fact that risk connectedness is critical to the Chinese economy when facing the impact of big events such as the Great Recession of 2007-2009 and the stock disaster in 2015. One key reason for the lack of empirical research work on Chinese market risk connectedness is the high dimension of industry networks. Therefore, we should consider methods and approaches which can be applied to high-dimension data to figure out the internal mechanism of the Chinese market risk connectedness.

In the thesis, I progress on both the methodological and substantive fronts. On the methodological side, I handle the dimensionality problem based on the

Diebold–Yilmaz connectedness measurement frameworkDiebold & Yilmaz (2012), which is intimately related to the key feature of network analysis (the network structure, the degree distribution, and the key measure of network centrality, the mean degree). Particularly, I do so by estimating the network using LASSO methods, which facilitates high dimensionality through selecting and shrinking. On the substantive side, no longer constrained by the dimensionality problem, I perform a Chinese market risk connectedness analysis. In particular, I characterize the static and dynamic high-frequency stock return risk connectedness of SWS secondary industry, 2010–2020.

In the next section, I will give a literature review of the work related to risk connectedness. In section 3, I will introduce the data used in the research. In section 4, I briefly summarize the Diebold–Yilmaz connectedness measurement framework and introduce VAR-Lasso model as the foundation of empirical approximating approach in the Diebold-Yilmaz framework. In Section 5, I provide the result of both static and dynamic analysis of the Chinese market, and I conclude in Section 6. The key section is section 5, which answers two questions: i) How risk is transmitted and spread in the economy? ii) What are the feature of an economy under high risk and low risk regarding the industries?

2 Literature Review

Risk connectedness is mentioned by Jackson (2010) for the first time. Specifically, they present an economic model of systemic risk in which the undercapitalization of the financial sector as a whole is assumed to harm the real economy, leading to a systemic risk externality. They define system risk as to the risk of collapse of the entire market, as opposed to the risk associated with the individual component in a system. Also, they find that financial regulation should be focused on limiting systemic risk, that is, the risk of a crisis in the financial sector and its spillover to the economy at large. In economics, there are two major types of risks, one is systematic risk and the other is idiosyncratic risk. In the work of Acemoglu et al. (2012), they demonstrate that in the presence of intersect-oral input–output linkages, micro-economic idiosyncratic shocks may lead to aggregate fluctuations. Furthermore, they have shown that micro-economic idiosyncratic shocks can lead to systematic risks, which is evidence of the statement that risk originated from one field can then be transmitted to other fields or industries, which becomes the systematic risk. Here comes a new question: Can we predict a future economic downturn with systematic risk? Babus (2013) has successfully answered the question. They derive a measure of aggregate systemic risk called CATFIN that complements systemic risk measures by forecasting macroeconomic downturns six months into the future using out-of-sample tests conducted with U.S., European, and Asian data. The result shows that the measure designed in Babus (2013) can forecast macroeconomic declines in financial institutions but has not marginal prediction ability for both non-financial firms and simulated 'fake financial institutions'. The concept of systemic risk discussed in Acemoglu et al. (2012) and Babus (2013) are similar. Babus (2013) focuses on the general definition of systemic risk and how the concept can be applied to finance, but Acemoglu et al. (2012) focuses on the relationship between systemic risk with economic depression. Those two papers can demonstrate the central concept of my paper -

systemic risk, but they both do not cover all industries in the market. Thus, I want to extend the content of systemic risk analysis to a wider range, which involves most of the industries in the market. To study the relationship between different components of the market, I need to demonstrate how they are connected, that is, connectedness.

Regarding risk connectedness, people research two aspects, one is a contagion, another is the transmission. The contagion side focuses on the return rate and tries to figure out how the risk connectedness rises under shocks from a specific source. However, the transmission side focus on volatility, that is, how the connectedness fluctuates under a certain period. Five approaches have been taken to analyze the risk connectedness in previous research, which are correlation coefficients among markets Goetzmann et al. (2001), ARCH model and GARCH model Engle et al. (1987), contagious model Eichengreen et al. (1996), cointegration and VAR model Cologni & Manera (2008), and direct analysis under special transmission mechanism Gertler & Gilchrist (1993).

The first approach Goetzmann et al. (2001) first examines the correlation coefficients between two markets within a stable period, and finds that the correlation coefficients significantly rise after shocks. The author Goetzmann et al. (2001) collected data from 12 stock markets and test the contagion of stock crises in 1987. The correlation coefficients, according to the research of the author, rose from 0.23 to 0.39 after the stock crisis. They also test the effect of the approach on the Mexico financial crisis, which gives a similar conclusion as the first case. However, other scholars argue that the rise in correlation coefficients cannot be evidence of risk connectedness since the correlation coefficients are based on the volatility of the market and people should eliminate the bias caused by the volatility. Based on the research of Egert & MacDonald (2009), the correlation coefficients did not show a significant increase after the Asian financial crises in 1997, the Mexico financial crises in 1994, and the stock crises in 1987.

For the second approach, Engle et al. (1987) used the GARCH(1,1)-M model to examine the var-covar risk transmission mechanism among major stock markets (US, Japan, UK) during the stock crises in 1987. Specifically, they study the price change between open price to close price and close price to open price instead of close price to close price. The conclusion is that the transmission mechanism was found from New York to London and Tokyo, from London to Tokyo. However, the conclusion did not hold from the reversed direction. Plus, they also utilized a bivariate GARCH(1,1) model to analyze the effect of the yield curve of the US and Japan on Hong Kong, Korea, Singapore, Thailand, Malaysia, and Taiwan. The result shows that the volatility of those markets is influenced by both international factors and local factors but the international factor has a deeper influence on the markets. Other than the international factor and the local factor, they also find that specific events can influence the market such as the invention of national funds, the fraction of trade in the economy, and the fluctuation of the exchange rate.

Regarding the third approach, Eichengreen et al. (1996) divide contagion into two types, one is contagion within an overlapped period (US and UK), another is contagion within a non-overlapped period (the UK and Japan). Based on the contagious model, the author assumes that the market is influenced by both systematic risk and idiosyncratic risk from the local market and foreign market. The result of the three-stage model before and after the stock crises demonstrates that the contagious coefficients from New York to London and Tokyo, from London to Tokyo have significantly been increased.

For the fourth method, the author used the VAR model and co-integration to analyze the connectedness between markets. This approach, which can be the optimal choice for most of the studies in the field, is also the major model utilized in my research. The author has found that the stock index of the US has a huge influence on the stock index of other countries after October 19, 1987. The author also introduced the covariance matrix to represent the level of aggregation of the capital market. Based on the result of VAR, the author developed a multi-factor model, which shows that the change in factor volatility leads to the change in return volatility. Furthermore, they find a huge jump in the stock market volatility after the crises in 1987 and the conclusion can be found not only in the stock market but the derivatives market.

The last method is used to find the reason for the vulnerability of the financial market in a country. In the work of Gertler & Gilchrist (1993), a bivariate probit model is utilized to predict the probability of industrial crises in both 1959 and 1993. They find that the probability they are interested in has a direct correlation with the probability of speculation in other countries. Other mathematical methods are used in the research of risk connectedness. For example, the author of Billio et al. (2012) used the Granger Causality test to detect whether there is an obvious delay effect in the stock crises.

In the work of Diebold & Yilmaz (2012), the author utilized the VAR-Lasso model proposed by Hsu et al. (2008) and regard the result of variance decomposition as the pairwise connectedness between different banks abound the world. To be more specific, the author uses VAR-Lasso methods to shrink, select, and estimate the high-dimension network data of the world's top 150 banks from 2003 to 2014. With this model, the author tells us how risk is transmitted in the global bank network. In particular, the paper contains both static analysis and dynamic analysis. In the static analysis, the author compares the network for risk transmission before and after the financial crisis in 2008, which is a globally big event. The result shows that the model can demonstrate the risk transmission process in the bank network. One similar paper compared to Diebold & Yilmaz (2012) is the work of Acemoglu et al. (2012), they use the risk connectedness framework of Demirer et al. (2018) to investigate connectedness in the Chinese banking system based on daily range-based volatility series of 14 publicly-traded commercial banks from 2008 to 2016. Statically, they find a positive rank correlation between the size and risk connectedness of banks. Their findings suggest that a bank might be "too big to fail," but not necessarily "too interconnected to fail" and vice versa, and that these two cases may coexist conditional on the system being in distress. According to Demirer et al. (2018), three key characteristics are often used in the network analysis. The first one is **degree of centrality**, which is the number of nodes directly connected to a node. Suppose we are in a social network, nodes represent people and edges represent friend relationships. With a greater degree of centrality of a node, we can say that the person has more friends and that person may be a more prestigious person than others. The second one is **closeness centrality**, which indicates the sum of the shortest distances from one node to all other nodes, or the inverse of the sum. Generally speaking, close centrality is the reciprocal of the sum, which means that the value of close centrality is between 0 and 1. The greater the close centrality, the closer the distance between this node and all other nodes. Tight centrality characterizes the nature of a node to all other nodes. In social networks, a larger closeness centrality of one person means that a person can quickly connect with all people. The last one is **betweenness centrality**, which is one of the measurement standards for the centrality of network graphs based on the shortest path. For a fully connected network graph, where any two nodes have at least one shortest path, the shortest path in the weightless network graph is the sum of the number of edges contained in the path, and the shortest path in the weighted network graph is the weight of the edges contained in the path Sum up. The betweenness centrality of each node is the number of times these shortest paths pass through the node. Betweenness centrality has a wide range of applications in network theory since it represents the degree of interaction between a node and other nodes. Plus, betweenness centrality is used as a common measure of centrality, and it is suitable for solving many problems in network theory.

Additionally, Diebold et al. (2017) uses variance decomposition from high-dimensional vector autoregressions to characterize connectedness in 19 key commodity return volatility, 2011-2016. They study both static (full-sample) and dynamic (rolling-sample) connectedness and they summarize and visualize the results using tools from network analysis. The results reveal clear clustering of commodities into groups that match traditional industry groupings but with some notable differences. The energy sector is most important in terms of sending shocks to others, and energy, industrial metals, and precious metals are themselves tightly connected. In the following content of the thesis, I will follow the framework of Diebold and identify the systematic risk and the idiosyncratic risk respectively.

3 Data

I obtain the data of 104 industries from the SWS (Shen Wan Security) secondary industry index, from October 12, 2015, to May 31, 2020. The SWS industry index is developed by SW company, which is a security company in China. The index covers all secondary industries in China and provides a profile of each industry. The data is in classical OHLC format, which contains high price, low price, open price, and close price during the day. However, I find that 8 industries in the data contain missing values and most of them are 100% missing. Since I do not have enough information to fill in the missing values, I decide to remove them to avoid problems of the empirical analysis. Before constructing the model, I have to transform the OHLC data into another format. Following Garman & Klass (1980), Daily stock volatility is calculated as

$$\widetilde{\theta}_{it}^2 = 0.511(H_{it}-L_{it})^2-0.019[(C_{it}-O_{it})(H_{it}+L_{it}-2O_{it})-2(H_{it}-O_{it})]-0.383(C_{it}-O_{it})^2 \quad (1)$$

where $H_{it}, L_{it}, O_{it}, C_{it}$ are, respectively, the logs of daily low, opening, high, and closing prices for $industry_i$ on day_t. The return volatility based on the equation above is shown in Table 1.

Date	Insurance	Oil	Railway Transportation	Airports
2010-10-12	-0.164	-0.105	0.049	0.022
2010-10-13	0.162	-0.036	-0.165	0.008
2010-10-14	-0.091	0.097	-0.008	-0.100
2010-10-15	0.11	-0.001	0.187	0.123
2010-10-16	-0.035	0.045	0.092	-0.063
2010-10-17	0.017	-0.111	-0.150	-0.024
2010-10-18	-0.106	0.053	-0.070	0.061
2010-10-19	0.011	0.135	0.146	-0.019
2010-10-20	0.047	0.043	0.005	-0.071

Table 1: Example of the Return Volatility

Based on the literature review, risk connectedness can be represented by the return volatility so return volatility is of direct interest in financial markets. The volatility tracks invest fear, the risk connectedness is fear connectedness Diebold et al. (2017). Thus, return volatility can be an excellent tool from the perspective of real-time crisis monitoring. In other words, we can detect both crises and upswings if the volatility moves along with the upcoming crises. Here, we use range-based return volatility. According to Demirer et al. (2018), range-based realized volatility has the same efficiency as realized volatility based on high-frequency intra-day sampling, but it requires only four readily available inputs per day, and it is robust to certain forms of microstructure noise. Another reason for the use of return volatility is that the use of volatility in risk connectedness analysis can help to detect the origin of the risk, as volatility jumps more during the big events or crises and the VAR approximating model is used in the analysis.

4 Methods

4.1 Diebold–Yilmaz volatility connectedness framework

Here, I will introduce the Diebold–Yilmaz volatility connectedness framework, which serves as the fundamental method of the full model. The framework is about connectedness measures based on variance decompositions, which is proposed and developed by Klößner & Wagner (2014) and Demirer et al. (2018).

Connectedness measures based on variance decompositions are practical and simple. First, they are directly linked to modern network models, and they are also related to systemic risks, such as marginal CoVaR Adrian & Brunnermeier (2011) and ES Acharya et al. (2017). Secondly, different connectedness at different horizons[2] are allowed, leading to the selection of a preferred horizon and the examination of a variety of horizons if desiredDemirer et al. (2018). For example, the 20-day connectedness might be significantly different from the 1-day connectedness. Finally, they make obvious intuitive sense, answering a key question, which at the most granular pairwise level is "How much of entity i's future uncertainty (at horizon H) is due to shocks arising not with an entity I, but rather with entity j?".

I conduct the variance decomposition based on the VAR model. In time series analysis, the auto-regression representation is $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$, where $\varepsilon_t \sim (0, \Sigma)$. And the moving average representation is $x_t = \sum_{i=0}^{p} \mathbf{A}_i \varepsilon_{t-i}$, where the $N \times N$

[2]Horizon indicates the window of the estimation. For example, we can estimate the connectedness under a 30-day window or a 90-day window.

coefficient matrix $\mathbf{A}_i$ obey the recursion $\mathbf{A}_i = \Phi_1\mathbf{A}_{i-1} + \Phi_2\mathbf{A}_{i-2} + ... + \Phi_p\mathbf{A}_{i-p}$, with $\mathbf{A}_0$ an $N\times N$ identity matrix and $\mathbf{A}_i = 0$ for $i < 0$. Identification of the lagging parameter becomes challenging in the high-dimensional situations, which is the key question I want to answer in the paper. Here, I follow Diebold & Yilmaz (2012) in using the "generalized identification" framework of Pesaran & Shin (1998), which produces variance decomposition invariant to rank. Instead of attempting to orthogonalize shocks, the generalized approach allows for correlated shocks but accounts appropriately for the correlationDiebold & Yilmaz (2012).

Once we have built the $VAR(p)$ model, we can then use the variance decomposition method to produce the decomposition matrix, which will be used in the connectedness measures. For a $VAR(p)$ model, we have the following form.

$$y_t = u + \mathbf{A}_1 y_{t-1} + ... + \mathbf{A}_p y_{t-p} + \epsilon_t \tag{2}$$

We can make a decomposition on the form and it is shown below. The matrix A will be used in the following approach.

$$\mathbf{Y}_t = \mathbf{V} + \mathbf{A}\mathbf{Y}_{t-1} + \epsilon_t \tag{3}$$

$$A = \begin{bmatrix} A_1 & A_2 & \dots & A_{p-1} & A_p \\ \mathbf{I}_k & 0 & \dots & 0 & 0 \\ 0 & \mathbf{I}_k & & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & \mathbf{I}_k & 0 \end{bmatrix}$$

where Y is a p-length vector, V and ϵ_t are vectors of 0's except the first element in the vector.

4.2 Risk Connectedness Measures

In this part, I want to introduce the risk connectedness measures. Let's begin with the pairwise directional connectedness, and proceed with total directional connectedness to calculate the systematic connectedness.

Suppose we are in a huge market network, node $j's$ contribution to node $i's$ H-step-ahead generalized forecast error variance, $\Theta_{ij}^{g}(H)$, is

$$\theta_{ij}^{n}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)}, H = 1, 2, ... \tag{4}$$

where θ_{jj} is the standard deviation of the disturbance of the jth equation Σ is the covariance matrix of the disturbance vector ε, and e_i is the selection vector with one as the ith element and zeros otherwise.

Next I normalize each entry of the generalized variance decomposition matrix

(Equation 3) by the row sum to obtain pairwise directional connectedness from node j to node i:

$$\widetilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{5}$$

As a matter of notation, I now convert from $\widetilde{\theta}_{ij}^{g}(H)$ to $C_{i \leftarrow j}^{N}$ (C is, of course, for risk connectedness), which is more directly informative.

After obtaining the pairwise directional risk connectedness measure $C_{i \leftarrow j}^{N}$, I can move to total directional risk connectedness measures. Total directional risk connectedness to node i from all other nodes j is

$$C_{i \leftarrow \bullet} = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ij}^{g}(H)} = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\theta}_{ij}^{g}(H)}{N}. \tag{6}$$

Similarly, total directional risk connectedness from node i to all other nodes j is

$$C_{\bullet \leftarrow i} = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ji}^{g}(H)} = \frac{\sum_{j=1, j \neq i}^{N} \widetilde{\theta}_{ji}^{g}(H)}{N}. \tag{7}$$

Finally, I obtain the systematic connectedness measure. Using the normalized entries of the generalized variance decomposition matrix (Equation 2), I measure total directional risk connectedness as

$$C^H = \frac{\sum_{i,j=1,j\neq i}^{N} \widetilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}_{ji}^{g}(H)} = \frac{\sum_{i,j=1,j\neq i}^{N} \widetilde{\theta}_{ji}^{g}(H)}{N}. \tag{8}$$

The total risk connectedness is also called *systematic* connectedness. It is simply the sum of total directional risk connectedness whether "to" or "from." Those measures might be abstract for beginners so I give the further interpretation. Suppose we now focus on two industries, bank i and insurance j. The measure $\widetilde{\theta}_{ij}^{g}(H)$ represents the risk transmitted from bank to insurance and we can generate a risk connectedness matrix, which is similar to a correlation matrix or covariance matrix. Then, the notation $C_{i\leftarrow\bullet}$ represents all risk connectedness bank field receives from other industries in the network/market. Similarly, the notation $C_{\bullet\leftarrow i}$ represents the risk connectedness that bank sends to other industries. As for the total risk connectedness, we can simply regard it as how the bank industry or insurance industry gets involved in the risk transmission process.

4.3 Volatility Connectedness Estimation with High-Dimension VAR

So far I have discussed Diebold–Yilmaz volatility connectedness measurement-Demirer et al. (2018) and the connectedness measure. Now I want to discuss the estimation of high-dimension VAR with LASSO, which can be useful in the high-dimension network analysis.

I conduct the connectedness assessment on an estimated VAR approximating model. Due to the high-dimension property of the data, I need the VAR to be estimable in high dimensions, somehow recovering degrees of freedom Demirer et al. (2018). People can do so by purely using the shrinking method (such as ridge regression) or purely using the selection method (such as traditional criteria like AIC, BIC, or SC). However, combining shrinkage and selection with variants of the LASSO is particularly crucial[3]. To understand the LASSO, consider the OLS estimation:

$$\widetilde{\beta} = \arg\min_{\beta} \sum_{i=1}^{T} (y_t - \sum_{i} \beta_i x_{it})^2 \tag{9}$$

subject to the constraint:

$$\sum_{i=1}^{K} |\beta_i|^q \leq c. \tag{10}$$

Equivalently, consider the penalized estimation problem:

$$\widetilde{\beta} = \arg\min_{\beta} [\sum_{i=1}^{T} (y_t - \sum_{i} \beta_i x_{it})^2 + \lambda \sum_{i=1}^{K} |\beta_i|^q]. \tag{11}$$

Concave penalty functions are non-differentiable at the origin point, which produces selection. However, the smooth convex penalties (e.g., q = 2, the ridge regression estimator) can produce shrinkage. Hence penalized estimation can com-

[3]Lasso regression and ridge regression belong to the same method family (elastic net) and we move from lasso to ridge by changing only one parameter α

bine the advantage of both selection and shrinkage. To have a better understanding of the difference between ridge regression and lasso regression, the figure.2 below can help.

The LASSO algorithm introduced in the seminal work of Tibshirani (1996), solves the penalized regression problem with q = 1. Hence it shrinks and selects. Moreover, it requires only one minimization, and it uses the smallest q for which the minimization problem is convexDemirer et al. (2018).

An extension of the LASSO, the so-called adaptive elastic net (Zou & Zhang, 2009), not only shrinks and selects, but also has the oracle property. In the implementation of the adaptive elastic net, I solve

$$\widetilde{\beta}_{AEnet} = \arg\min_{\beta}[\sum_{i=1}^{T}(y_t - \sum_{i}\beta_i x_{it})^2 + \lambda\sum_{i=1}^{K}\omega_i(\frac{1}{2}|\beta_i| + \frac{1}{2}\beta_i^2], \tag{12}$$

where $\omega_i = 1/|\widetilde{\beta}_{i,OLS}|$, and λ is selected equation by equation by 10-fold cross-validation. Note that the adaptive elastic net penalty averages the “LASSO penalty” with a “ridge penalty,” and that it weights the average by inverse ordinary least squares (OLS) parameter estimates, thereby shrinking the “smallest” OLS-estimated coefficients most heavily toward zero. For the VAR-Lasso model, the number of parameters being estimated is 97×97, that is, each pair of industries and the connectedness inside one industry are estimated in the model to generate a network. Recall the $VAR(p)$ introduced in the previous section, the form of the model is shown in Equation 13.

$$\mathbf{Y}_t = \mathbf{V} + \mathbf{A}\mathbf{Y}_{t-1} + \lambda\mathbf{w}(\frac{1}{2}|\mathbf{A}| + \frac{1}{2}|\mathbf{A}|^2) + \epsilon_t \tag{13}$$

4.4 Network Model

The issue of how to display results takes on great importance in high-dimensional network analysis. Network analysis is an important part of social science research, which typically focuses on the social network such as the relationship between people or firms. There are mainly two types of networks, directed graph, and indirect graph. For a directed graph, we assume the effect from node A to node B does not indicate the effect from node B to node A. However, we can assume the effect is symmetric in an indirect graph. In the subsequent work, I will construct a network connectedness model with 97 nodes. However, presenting and examining $97 \times 97 = 9409$ estimated pairwise variance decompositions would be thoroughly uninformative. Therefore, I characterize the estimated network graphically using five instruments: side color, node size, node color, node location, and link arrow sizes. Throughout, I use the open-source Gephi software (https://gephi.github.io/) for network visualization. Next, I want to explain the detailed information of each graphical representation of the network model. In figure 2, the color bar is provided. From left to right, we can regard the movement as a signal of "higher degree". For example, if the side color moves from red to blue, the risk connectedness should rise from low level to high level.

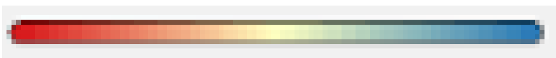

Figure 2: Color in the Network Plot

Side color indicates relationship between two industries Side color is the most important sign for my analysis since it indicates the level of risk connectedness in the network/market. However, we might not have a clear idea about the relationship between the two specific industries since the number of edges is large. Thus, we should focus on the overall color of the network.

Node size indicates the impact to others Node size is a good indicator of key industries because it represents the impact from the node to other industries. If we find a large node, we should assume the industry performs as a core node in the risk transmission process.

Node location indicates average pairwise directional connectedness I use the ForceAtlas2 algorithm in Gephi to determine the node position. This algorithm can help to find a stable state and accurately balance the repulsive force and attractive force. This stable state makes the two nodes repel each other like the same magnetic pole, and the link between the nodes attracts each other like an elongated spring. It is worth noting that the attractive force between the links is proportional to the pair-wise average conduction effect. In addition, the steady-state node position depends on the initial node position, so the final result is not unique. Based on the research purpose of this article, I am interested in the relative rather than absolute equilibrium node position between the nodes, so the difference of the initial nodes can be ignored.

Node color indicates the volatility of each industry Node color represents the volatility/risk inside an industry. We use node color because we cannot generate an edge from node A to node A. Similar to the setting to edge color, the internal

Sign	Meaning
edge color	pairwise connectedness between nodes
node size	impact from the node to other nodes
node location	correlation between nodes
node color	volatility of the node

Table 2: Symbols in the Network

volatility varies between low level and high level.

5 Result

5.1 Big Events from 2015 to 2020

Before both the static analysis and the dynamic analysis, I want to give a brief overview of the big events in the stock market from 2015 to 2020 so people can have a better understanding of how the return volatility and the risk connectedness changed or formed.

Stock crises in 2015: After July 2014, especially in October, the stock market had three huge increases in prices. Then, from November 2014 to June 2015, within about seven months, the Shanghai Composite Index rose from 2,450 to 5,166, which means that the cumulative increase in the stock price has been doubled (110.9), which is a 45% drop in price. The small and medium-sized board and the ChiNext fell by 44.6% and 51.8% respectively[4]. Regarding the reason for the stock crises, six reasons are proposed by researchers. The first reason is that the market

[4]All the data above is provided by Liu & Woo (2018).

has overwhelming short-term expectations for Chinese economic reformation and growth pattern transformation, and the long-term expectations are insufficient, resulting in the eagerness for success, short-term speculation, rapid price increases, and rapid arbitrage. The second reason for the crises is that people have incorrectly understood the essence of the capital market and they regard the capital market as a field where they can push the price up to and earn profits. The third reason, which is the direct force leading to the crises, is the high leverage in the market. In other words, the rise in leverage rate can add considerably high risk to the market and bring about bubbles in the market. The fourth reason is the systematic weakness of the transaction mechanism, which includes the algorithmic transaction (quantitative trade and high-frequency trade), the impact of derivatives markets on the currency market, and the "T+1" transaction rule. The fifth reason is the lack of independent monitoring from the government. The last reason for the crises is the excessive exaggeration of the market optimism by major media, which has caused serious misleading to the market and constituted a public opinion factor for the outbreak of the market crises.

Trade War 2018: I have introduced the trade war between China and the US in the introduction part and the timeline is from July 2018 to June 2019. As mentioned in the introduction section, many important industries have been influenced by the trade war so we should find a high-risk connectedness in 2018 and 2019.

COVID Epidemic 2020: COVID-19 is also introduced in the introduction section and the timeline is from December 2019 to May 2020. Due to the shock of the epidemic, the Chinese economy has been negatively impacted and a high-risk connectedness should be expected during that hard time.

5.2 Static Analysis of Risk Connectedness

I estimate logarithmic volatility VARs using the lasso regression as described above. Then I conduct variance decomposition and get corresponding risk connectedness measures at horizon $H = 10$, using the estimated VAR parameters. Based on the result of variance decomposition, I draw the network graph of the whole market from 2015 to 2020 and I want to analyze the graph from two aspects. One is how each industry distributes in the network, that is, the clustering characteristic of each industry. Another one is to investigate which industry has performed as the intermediary node in the network, which means they are the most important nodes in the risk transmission process in the network.

5.2.1 Clustering analysis of industries

The clustering feature can help us figure out the potential transmission chains between industries. Here, the clustering feature is associated with a bunch of industries that are closely distributed in the network graph. Generally, the clustering feature will become more clear as the relationship among industries becomes closer, indicating a high-risk connectedness and leading to stronger risk transmission. The result shows that the industries in similar areas and close co-operations have clear clustering characteristics. Specifically, the clustering characteristic can be divided into the following seven categories and I will focus on the first two

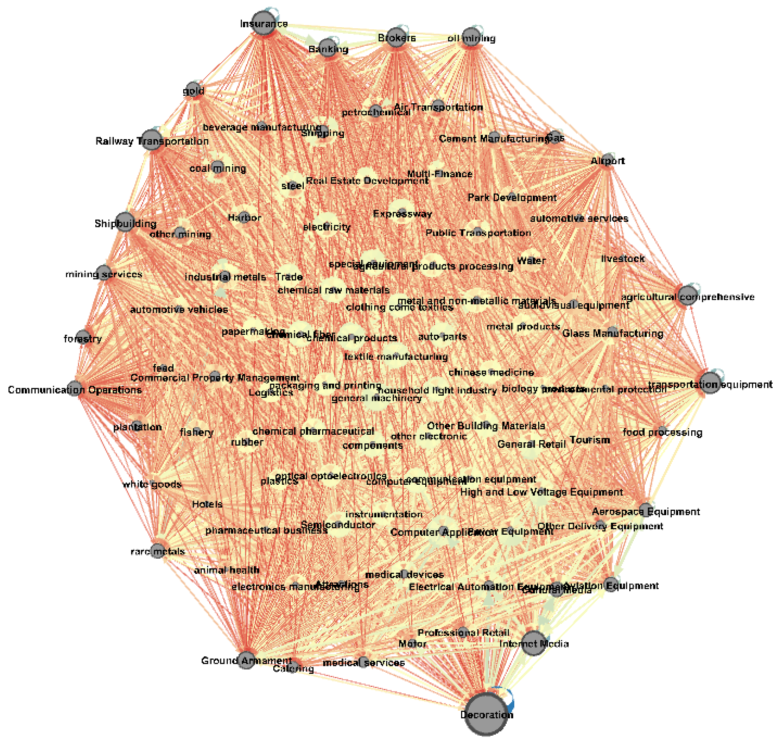

Figure 3: Risk Connectedness (2015-2020)

categories.

The first one is finance and real estate. In Figure 6, the clustering features between real estate development, diversified finance, insurance, banking, and broker are considered significant. Since real estate is a capital-intensive industry, its prosperity and development are inseparable from the financial support of the financial sector. Moreover, the prosperity of the real estate market is an important guarantee for investors to establish confidence, and therefore feeds back the development of financial markets. The close investment relationship between finance and real estate determines the fact that they prosper mutually, which indicates that if one

Cluster	Industry
I	finance, real estate
II	transportation
III	industrial materials, fuels, heavy industry
IV	entertainment, consumption
V	agriculture
VI	electronic device
VII	medicine

Table 3: Clustering Characteristic

of them becomes risky, the other one is less likely to survive from the risk. Most real estate firms, in China, have owned an independent capital subsidiary and the function of the subsidiary is to accumulate capital for the parent company. Additionally, some financial companies, such as Citic Group, also own a real estate company. From the perspective of the structure of the market, a financial company is inseparable from a real estate company so we can find a clustering characteristic in the graph between the two industries.

The second one is transportation, including transportation equipment, air transportation, railway transportation, ports, airports, and shipbuilding industries. The various components in transportation are mutually constrained and interdependent. Those transportation industries are crucial in the whole market since they are the basic pipelines that link each industry or cluster in the network. People and goods are transported through those sub-industries and the real economy including agriculture, manufacture, medicine is operated based on transportation. Thus, they will become one of the clusters that greatly facilitates the risk connectedness when encountering big events. For example, affected by the blockage of the Suez Canal, international oil prices fluctuated significantly. The

Suez Canal is one of the most important energy-transportation channels in the world. It is the fastest route to transport crude oil from the Middle East to the European coast of the Mediterranean Sea. As the world's largest oil consumption region, Europe is highly dependent on Middle East oil. Therefore, the Suez Canal is the lifeline of European energy. Once shipping returns to normal, the relationship between supply and demand will return to normal, so the price drop is in line with market logic. From the example of the Suez Canal, we can easily understand how crucial transportation is for other industries.

The third category includes industrial materials, fuels, and heavy industry, such as oil exploration, petrochemicals, chemical materials, gas, steel, metal and non-metal materials, industrial metals, gold, rare metals, and other industries. Similar to the function of transportation, industrial materials provide fundamental goods to all industries.

The fourth category contains entertainment and consumption, including hotels, tourism, attractions, restaurants, etc. Those industries are naturally linked since people always make a plan to travel, eat, live in the hotel, and visit attractions.

The fifth category includes agriculture, plantation, livestock and poultry breeding, agricultural integration, fisheries, agricultural products processing. Those industries are all in the range of primary industry so we can find a clustering characteristic among them.

The sixth category contains electronic devices. For example, computer applications, computer equipment, electronics manufacturing, electronic appliances, etc.

Industry	Risk Connectedness	Industry Risk
Oil	0.48	0.03
Bank	0.63	0.12
Insurance	0.52	0.07
Railway Transportation	0.44	0.02
Ground Equipment	0.02	0.34
Aviation Equipment	0.01	0.29
Mining Services	0.02	0.39
Transportation Equipment	0.04	0.34

Table 4: Risk Connectedness Effect and Industry Risk

The seventh category includes medical care, medical services, medical devices, Chinese medicine, pharmaceutical industry, chemical pharmaceuticals, animal health, etc. For this category, I will assume the clustering characteristic becomes more clear during the COVID-19.

With the characterization of an industry cluster, I can conclude that the risk connectedness can be realized by the cooperation between industry clusters, which can be either the cooperation between individual industries in a single cluster or cooperations between two and more industries in each cluster. Furthermore, when risk emerges in one cluster, other industries in the same cluster will be affected at first, then the risk should be transmitted to closed clusters.

5.2.2 Intermediary Analysis of Risk Connectedness

As mentioned in the method section, there two types of risk in the analysis. One is the risk transmitted from or to other nodes (risk connectedness) and the other is the risk inside an industry (industry risk). Based on Table 4, we can find that four industries with the greatest risk connectedness are oil exploration, banking, insurance, and railway transportation. It should be noticed that the indirect risk transmission effects in the risk connectedness process are very common. Taking the oil exploitation industry as an example, the oil transmission industry has a significant risk transmission effect on the petrochemical, industrial metal, and insurance industries, but the direct transmission effects on other industries are not significant. Here, direct transmission means that the risk moves from one node to another node without reaching other nodes and indirect transmission means that the risk will pass through other nodes before arriving at the final node. For one thing, when risks occur within the oil extraction industry, it is directly transmitted to another node. For another, the oil industry transmits risks to the entire market through the inter-linkages of petrochemical, industrial metals, and insurance. Indirect risk connectedness is more influential than direct risk conduction since the extent and magnitude of transmission are much larger. Similarly, for banking, insurance, and railway transportation, we have the same transmission mechanism. Once one of those fields experiences a shock, the risk can be transmitted through either direct channel or indirect channel. In the analysis above, we are assuming the shock comes from an unknown field, which means it is an exogenous variable. However, we should always figure out the source of the risk, which is the shock. Otherwise, the market could experience the same type of risk next time.

One key question we need to answer is whether the risk comes from the nodes with the greatest risk connectedness. The risk of a single industry can be measured through the return volatility of the industry index. Thus, the risk characteristics of a single industry are conducive to finding the source of risk. Based on Table

4, the four industries with the highest risk are transportation equipment, ground equipment, aviation equipment, and mining services. Conversely, the average risk of the four industries with the highest transmission effects (insurance, banking, oil exploration, and rail transportation) is particularly small, indicating that the four industries themselves have few risks. Therefore, the risk transmitted by these industries is more likely from other industries and we know the risk has nothing to do with the node with the greatest risk connectedness effect. For example, in the transportation equipment, though the transportation equipment industry itself has no significant effect on the total risk connectedness to other industries, its own risk is large, and it will indirectly export risks to the entire market through one important industry - railway transportation. Based on the result above, some important industries can act as risk-transfer mediators, channeling the risks of the risk-source industry to the entire market. For governments, they must pay attention to those important industries mentioned above, take measures to monitor those industries, and mitigate risks before they are transmitted to the whole market.

5.3 Dynamic analysis of risk connectedness

In this section, I will first conduct a rolling window algorithm to process the data and generate the overall risk connectedness[5] in the market from 2015 to 2020. Then, I will estimate, respectively, the connectedness network before and after COVID-2019. By comparing two network models, I can figure out how the

[5] The overall risk connectedness is the average risk connectedness in the market, which measures the risk connectedness in the market at a certain time.

COVID-19 has activated the risk transmission in the Chinese market.

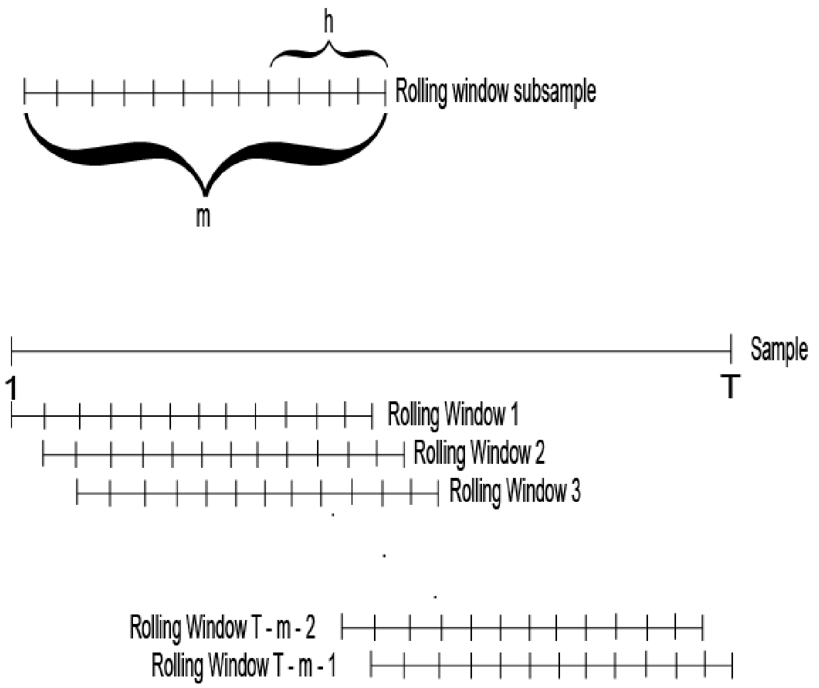

Figure 4: Rolling Window Estimation from Swanson (1998)

According to Zivot & Wang (2007), there three steps to perform a rolling window estimation.

Step 1: Choose a rolling window size, m, i.e., the number of consecutive observations per rolling window. The size of the rolling window will depend on the sample size, T, and periodicity of the data. In general, you can use a short rolling window size for data collected in short intervals, and a larger size for data collected in longer intervals. Longer rolling window sizes tend to yield smoother rolling window estimates than shorter sizes.

Step 2: Suppose that the number of increments between successive rolling windows is 1 period, then partition the entire data set into $N = T + 1 - m$

subsamples. The first rolling window contains observations for period 1 through m, the second rolling window contains observations for period 2 through $m+1$, and so on. There are variations on the partitions, e.g., rather than roll one observation ahead, you can roll four observations for quarterly data.

Step 3: Estimate the model using each rolling window sub-samples.

Following the three steps, I get the overall risk connectedness from 2015 to 2020.

5.3.1 Overall Risk Connectedness in China from 2015 to 2020

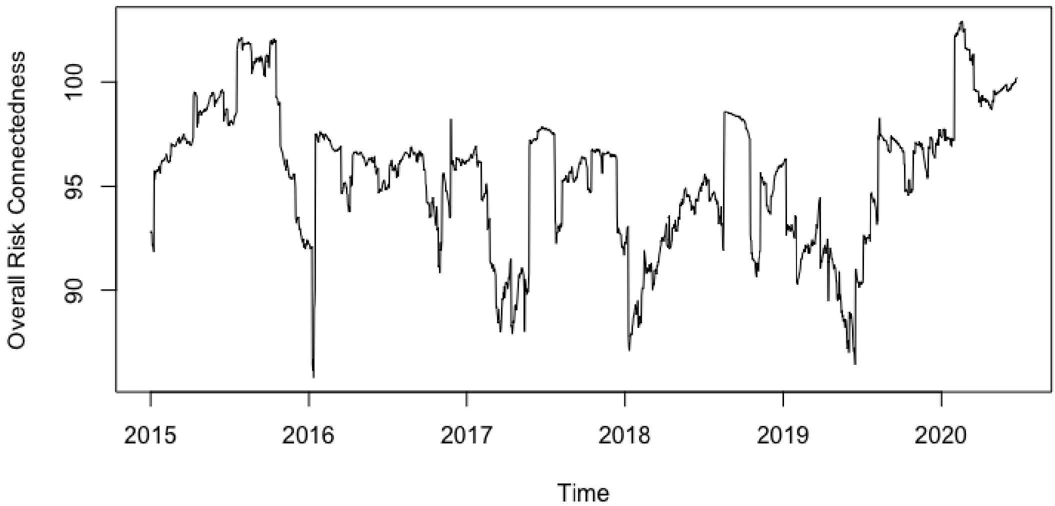

Figure 5: Overall Risk Connectedness from 2015 to 2020

I estimate the overall risk connectedness through the rolling window estimation and the overall risk connectedness is also called the systematic risk since the id-

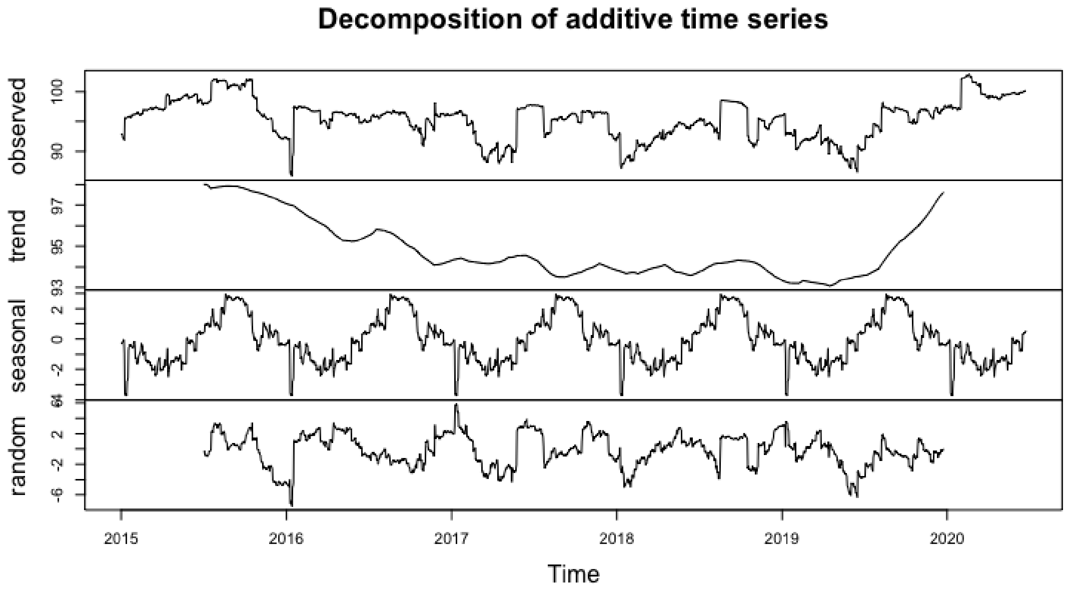

Figure 6: Decomposition of Overall Risk Connectedness from 2015 to 2020

iosyncratic risk is eliminated by average. Specifically, I choose 60 days as the rolling sample period and get the total risk connectedness, which continuously changes with time. The overall risk connectedness tells us how risky the whole market is in certain periods and it is a perfect measure to detect the relationship between the market with big events such as stock crises, trade war, and COVID-19. Then, I show the time series plot and decompose it to get the tendency, seasonality, and random effects [6].

In the graph of the overall risk connectedness, we can first notice a peak in the middle of 2015, which corresponds to the time of the stock crises in 2015. This is evidence for the proposition that the stock crises led to greater system risk in the market. Plus, we can find the risk connectedness was reduced quickly due to

[6]The time series decomposition is executed in R and the function is *decompose*(), which applies the "Seasonal and Trend decomposition using Loess"(STL) technique.

the policy of the government to save the stock market. Then, from the beginning of 2018 to the middle of 2018, we can find the risk connectedness has a huge rise, which might be caused by the activation of the trade war. However, the effect of the trade war is smaller than the effect of the stock crisis. It is possible because the trade war is a long-term event but the stock crisis is a short-term event. Plus, the tariff policy has a limited effect on the local market of China since the supply chain of China is complete and multiverse, which leads to stability and continuity of the market. From the end of 2019 to 2020, a huge increase in the risk connectedness has been caused by the COVID-19 epidemic in China. Especially in February and March, the risk connectedness reaches the highest level since 2015 and the hardest time for the epidemic is also February and March.

Based on the analysis above, the overall risk connectedness can accurately reflect the shock from a big event in the market.

5.3.2 Comparison before and after the COVID-19

In the second part of the dynamic analysis, I want to compare the overall connectedness before and after the COVID-19 in detail. From the beginning of January 2020 to March 2020, Covid-2019 shocked the whole of China. Start from Wuhan, Hubei, the disease killed around two thousand people in China and greatly depress every aspect of the countryHuang et al. (2020). By comparing the industry risk connectedness networks before and after the disease, we can analyze the influence of the risk transmission mechanism. From the comparison between graphs before and after the Covid-2019, one thing we can find is that both financial institutions and transportation departments play an important role before and after the disease. Also, the epidemic has boosted the emergence of risk in other areas such as forestry, agriculture, and the internet.

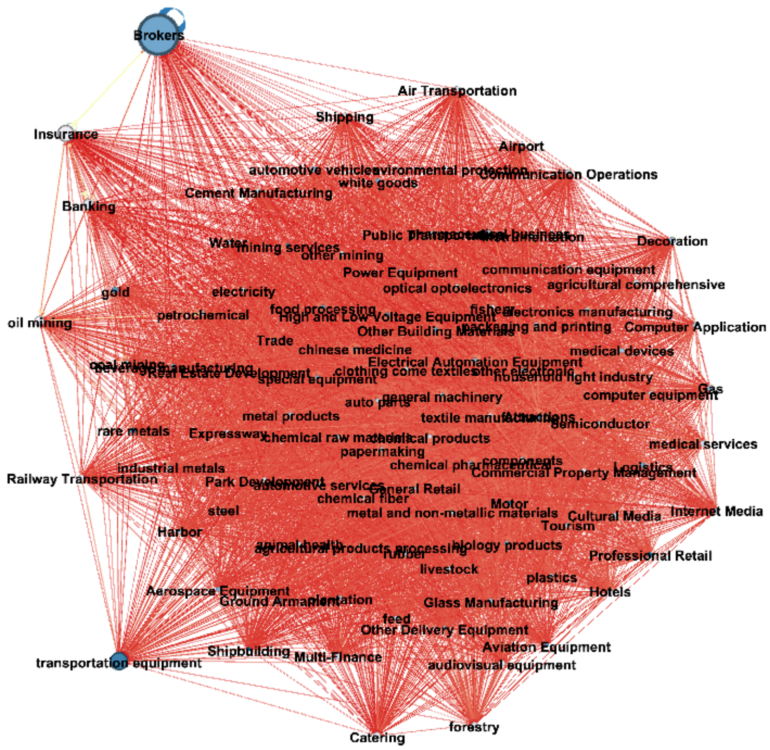

Figure 7: Risk Connectedness before Covid-19

For one thing, the risk connectedness effects become stronger among most industries after the COVID-19 since the overall color has changed, compared with the graph before the COVID-19, which is demonstrated in Fig.2. The Internet industry, for example, has much stronger transmission effects to others after the COVID-19. Plus, industry clusters have enhanced internal risk transmission effects. For example, ground military equipment, aerospace equipment, and aviation equipment present obvious clustering characteristics. Additionally, broker, oil

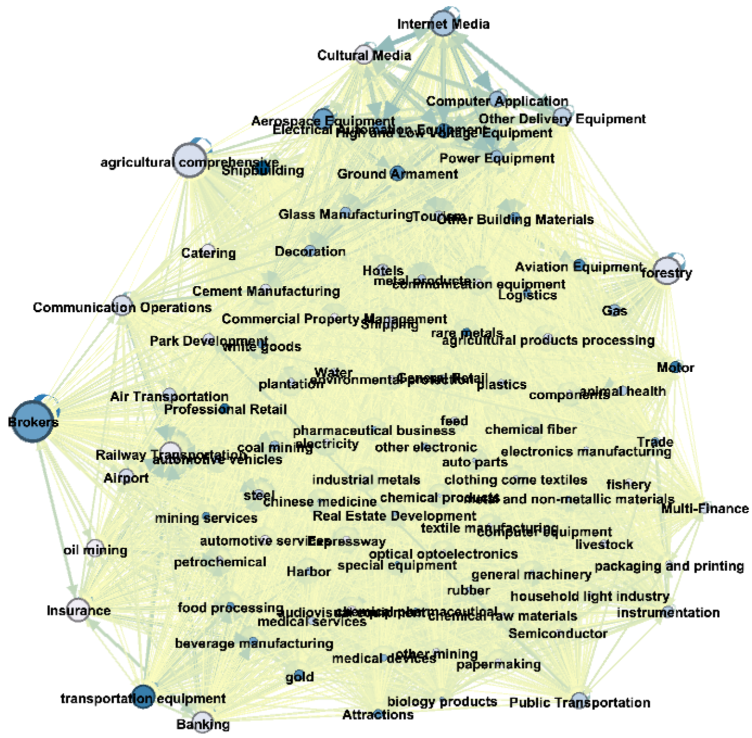

Figure 8: Risk Connectedness after Covid-19

exploration, insurance, and banking are closely related through remarkable connectedness relationships. That is to say, the volatility connectedness between individual industry and industry clusters is significantly enhanced, and the systemic risks of the entire industry are greatly invigorated after COVID-19 in 2020.

6 Conclusion

In the analysis of risk connectedness, the VAR-LASSO method is used to shrink, select, and estimate the high-dimensional network linking the SWS secondary industry index, 2015–2020. Based on the result of variance decomposition from the VAR-Lasso model, both static analysis and dynamic analysis are conducted. For the static analysis, seven types of clustering characteristics are found in the network graph of the Chinese stock market from 2015 to 2020. Plus, four intermediary nodes which act as the center to transmit risk but do not produce risk are found in the network. For the dynamic analysis, network connectedness is estimated with rolling-window estimation. I found that risk connectedness rises during big events, with clear peaks during the stock crises in 2015, the trade war in 2018, and COVID-19 in China. Particularly, industries including the Internet and cultural media are mostly influenced by the crash of COVID-19. Similar to the conclusion of static analysis, broker, banking, forestry, and other industries are nodes that transmitted risk in the network after COVID-19.

In the empirical analysis, I calculate and visualize the risk connectedness within the Chinese stock market. One thing we should notice is connectedness does not indicate causality. The risk connectedness I have discussed so far should be a type of correlation. This is because all the connectedness is indirect and we can always find a connectedness from node A to node B and vice versa. According to the theory of Ahelegbey & Giudici (2020), the result in the market (e.g. the color of the edge), might be driven by a common factor, which is the economic growth and that is why we find the edge colors all alter from red to yellow. However, the visualization of the network can be confusing since we cannot identify the difference of the edge color within a single graph. Another disadvantage of the analysis is that I do not include a detailed analysis of key industries. For example, further analysis can be conducted on the finance field, which includes a bank, insurance, security, etc. Plus, all the analysis is based on historical data but a model that can forecast the situation in the future will be more preferable. Thus, we can consider applying other methods to build a predictive model to help people avoid risk. Based on the result above, I have three suggestions for the management of risk connectedness. Firstly, the government should establish a better regulation system through security laws and improve the information disclosure mechanism. Those industries with high intermediary effect should receive more focus. Secondly, people should build up the right investing habits and avoid speculation and short-term investment in the industry with high risk connectedness. Thirdly, we should follow the rule of the market and the market cannot be the money machine utilized by the government or large business groups. Furthermore, the model we have developed in the thesis can be extended with modern time series models. For example, models of the GARCH family can be used to fit the volatility of a single industry that people are interested in and they can forecast the movement of future volatility to prevent high risk.

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