Risk spillovers among China’s financial institutions at times of Covid-19 crisis

Abstract: The Chinese capital market is undergoing accelerating reform, the interconnections among Chinese financial institutions are becoming closer, and the risk exposures are increasing. Based on the spillover index method and complex network model in the frequency domain of the TVP-VAR-DY model, we examine the volatility connectedness and the topological structure of 62 Chinese listed financial institutions during the COVID-19 crisis, including banks, securities, insurers, and diversified financials. We also use the quantile-on-quantile (QQ) approach to explore some nuanced features of the risk spillovers among financial institutions nexus and to capture the relationship in its entirety. The results reveal that the total volatility connectedness of the financial institutions markedly increase following the outbreak of COVID-19; Statically, banks and securities are the net transmitters during the COVID-19; Dynamically, the dynamic performance of different financial institutions during the COVID-19 pandemic is heterogeneous, and the possible driving factors are diverse. Moreover, from network analysis, we further find that the COVID-19 crisis has significantly changed the topological structure of the financial institutions, although the banks is highly systemically important institutions. During the COVID-19 crisis, the risk contagion ability of financial institutions in the network generally weak, then increase. Our findings may help researchers to understand the typical dynamics in the financial institutions and provide significant implications for portfolio managers, investors, and government agencies in times of highly stressful events like the COVID-19 crisis.

Key words: COVID-19; Financial institutions; Volatility spillover; Complex network

1. Introduction

The steady operation of financial institutions plays a significant role in economic development, while the collapses of Lehman Brothers result in the 2008 global financial crisis. After the US subprime crisis, "too big to fail" translated to "too connected to fail", and the connectedness of financial institutions would rapidly extend individual risk into systemic risk (Yang Zihui, 2020). Battaglia et al. (2014) point out that financial risk spillover means that a financial institution's risk in the financial system will spread to other financial institutions, causing a "domino effect" in the whole financial system. Risk contagion and risk spillover effects exist in the financial market, so it is necessary to effectively identify and avoid the characteristics of risk in the financial market (Gong Xiaoli & Xiong Xiong, 2020).

The COVID-19 outbreak and its rapid spread all around the world have significantly impacted the global economy. By the 30th of January 2020, the COVID-19 outbreak was defined as a PHEIC1. Besides, public health events seriously impact on capital markets and economies, which is difficult

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1 PHEIC :WHO identifies Public Health Emergency of International Concern as H1N1 influenza, Ebola, polio, and Zika virus (https://www.who.int/zh/).
to recover from within a given period of time (Yang Zihui et al., 2020). With the Russia-Ukraine conflict escalating, the global financial system are experiencing another turbulence. After invasion by Russia on 24th of February 2022, the financial market fluctuant, such as stock market and commodity market (Qureshi, 2022; Zaghum, 2022). Financial institutions frequently encounter risk, especially in the post-crisis period, which may confirm the concept of “too connected to fail”. In addition, the risk contagion of financial institutions has nonlinear, uncertainty and network characteristics. The financial institutions in China are divided into four sub-industries, including banks, securities, insurance, and diversified financials. These four sub-industries are closely related due to business transactions and other factors, which have risk contagion channels mainly in terms of liabilities and assets via network relationships. In addition, the correlation between financial institutions can be reflected in the stock market, and the spillover effects among financial institutions increase through stock price. The stock price of a financial institution falls, and then the stock price of related financial institutions also falls. Besides, the Chinese 14th Five-Year Plan requires strengthening the supervision of financial institutions, improving the identification, assessment, and prevention mechanisms of financial institutions.² It is therefore academically and practically essential to investigate the risk spillovers among the financial institutions, particularly over the COVID-19 period. Therefore, it is necessary to consider the impact of risk contagion of a single financial institution on the entire financial system, and the risk contagion between financial institutions brought about by the failure of a single financial institution deserves the attention of financial regulators.

Our work first links to a trending topic on financial institutions. In the existing literature there are many debates about the the performance of financial institutions under the conditions of the COVID-19 outbreak. As for the COVID-19 outbreak, researchers have mainly focused on the impact of the pandemic on the stock market and traditional financial market. Al-Awadhi et Al. (2020) point out that the increasing number of confirmed COVID-19 cases and deaths had a negative impact on the stock returns of the Hang Seng Index and the Shanghai Composite Index. A review of the literature has revealed that current studies in this field have predominantly focused on the impacts of natural disasters (e.g., earthquakes, tsunamis) on the financial market—few studies have focused on the impact of major public emergencies (Del Giudice & Paltrinieri, 2017). Adams et al. (2014) research showed that the cross-sectoral flow of credit funds between banks and insurers is accompanied by financial risk transmission, resulting in a significant cross-sectoral effect of systemic financial risk. Focusing on a single institution is likely to underestimate the risk spillover of financial institutions, thereby weakening the impact of financial risks on the real sector. Most of the research on financial network construction focuses on bank networks, and there are few related network constructions among different financial institutions. The risk contagion of financial institutions is affected by the degree of the network connection between institutions.

² Outline of the 14th Five-Year Plan and the Vision for 2035 for National Economic and Social Development of the People's Republic of China (https://www.gov.cn/).
Allen et al. (2019) pointed out that when a single bank experiences a crisis, other financial institutions in the network will share losses. Acemoglu et al. (2020) found that a tight financial institution network can reduce risk contagion. The opposite is true when the loss exceeds a certain threshold. Yang Zihui et al. (2018) measured the systemic financial risks of 56 Chinese listed financial institutions and found that there is apparent cross-sectoral risk contagion in the financial system from two perspectives, static and dynamic. Wu (2021) analyzed the overall and individual characteristics of the financial institutions, and found that the financial system is highly interconnected, particularly in extreme market conditions. Specifically, Fan et al. (2021) found that financial institutions have an increasing systemic risk according to the excessive network connectedness, and the banks had the largest risk spillover and highest system importance among financial institutions. Balachandran and Williams (2019) concluded that the underlying causes of the GFC are multiplicity and complexity and the capital market played an important role as signaler in the GFC, especially banks.

Our work is also related to the literature on the research methods, and there are two methods to generally measure the systemic importance of financial institutions. Kang and Ratti (2018) found that the spillover index method was better at estimating the fluctuation spillover relationship between the different elements. Based on the vector autoregressive model. Diebold and Yilmaz (2009) proposed the spillover index method to measure the return and volatility spillover of 19 global stock markets and Barunik and Krehlik(2018) mentioned time-frequency domain spillover index to address the dynamic linkages from different horizons. Then, Diebold et al. (2017) pointed out that the spillover index method and its variables can effectively detect and measure the volatility spillover effect between financial markets. Yang et al. (2019) used a modified spillover index to explore that China's financial institutions significantly influence on financial sectors in other major global economies. From a complex network perspective, Peron (2012) analyzed the relevance and stability of financial markets through changes in their network characteristics, such as their topology structure, topology index of nodes, and robustness (among others). Yang (2020) employed a lower tail network for 88 financial institutions in the USA and concluded that the increasing interconnection of financial institutions is an important factor in the outbreak of the subprime mortgage crisis. Xie(2021) used a time-varying t-copula model under network theory to construct a multiplex network of financial institutions to track the transmission path of risk, which found that the level of risk spillover has gradually increased under extreme events. The sample was divided into distinct parts to compare their spillover networks, which provide policymakers distinguish their short- and long-term policies(Li,2022; Li,2022). They achieved promising results, which provided the theoretical foundation for the current study.

The main contributions of the current study are as follows.

First, our work focus on how the COVID-19 crisis affected the connectedness among the financial institutions and evaluate the risk transmission across the financial institutions. In addition, we divide the Chinese financial institutions into four sub-industries, including banks, securities, insurance, and diversified financials, which can show the role of different businesses
in the financial system. The volatility spillovers among financial institutions may exhibit a differential pattern during the COVID-19 crisis, such as the rise of connectedness and the changes in spillover roles, which can provide a highly informative analysis for investors.

Second, this paper combines the spillover index method of Diebold and Yilmaz (2014) and the complex network method both from the static and dynamic perspectives, respectively. We conduct the time and frequency connectedness analysis in three ways: total connectedness analysis, dynamic total directional connectedness analysis and net connectedness analysis. Moreover, using network methods provide a visual cue of risk transmission paths among the financial institutions.

Our findings may help researchers understand the typical dynamics in the financial institutions and provide significant implications for portfolio managers, investors, and government agencies in times of highly stressful events like the COVID-19 crisis.

2. Research methods and variable selection

To explore the transmission mechanism among global stock sectors in a time-varying fashion, we use the TVP-VAR methodology of Koop and Korobilis (2014) and combine it with the DY method of Diebold and Yilmaz (2014). This framework extends the original DY method by allowing the variances to vary over time via a Kalman Filter estimation with forgetting factors. Therefore, the TVP-VAR based connectedness approach overcomes the shortcomings of using rolling window estimation (the results obtained from rolling window estimation is sensitive to the setting of the rolling window size and outliers, and easy to lose some observations) in the simple VAR based connectedness method (Liu and Gong, 2020; Gabauer and Gupta, 2020; Antonakakis et al., 2019; Antonakakis et al., 2018; Korobilis & Yilmaz, 2018).

According to the Bayesian Information Criterion (BIC), the TVP-VAR(1) model can be written as follows,

\[
Y_t = \beta_t Y_{t-1} + \varepsilon_t \quad \quad \quad \varepsilon_t \sim N(0, S_t) \tag{1}
\]

\[
\beta_t = \beta_{t-1} + \nu_t \quad \quad \quad \nu_t \sim N(0, R_t) \tag{2}
\]

\[
Y_t = \sum_{j=0}^{\infty} \A_t \varepsilon_{t-j} \tag{3}
\]

where \(Y_t, Y_{t-1},\) and \(\varepsilon_t\) are \(N \times 1\) dimensional vectors. The parameters \(\beta_t, \nu_t,\) and \(S_t\) are \(N \times N\) dimensional matrices, whereas \(R_t\) is an \(N^2 \times N^2\) dimensional matrix.

After estimating the time-varying coefficients and variance-covariance matrices, we need to transform the TVP-VAR to a TVP-VMA (vector moving average) using the Wold representation theorem in Eq.(3). Next, using the generalized impulse response functions (GIRFs) that represent the responses of all variables under a shock in variable \(i,\) we could estimate the impact of a shock
in variable $i$ to all other variables. Since we do not have a structural model, we compute the differences between an $h$-step ahead forecast with variable $i$ is shocked and not shocked. The difference can be accounted to the shock in variable $i$, which can be calculated as follows,

$$GIRF_i(h, \delta_{j,t}, F_{t-1}) = E(Y_{t+h} | \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}) - E(Y_{t+h} | F_{t-1})$$  \hspace{1cm} (4)$$

$$\psi_{j,t}^h(h) = \frac{A_{h,t}S_{j,t} \delta_{j,t}}{\sqrt{S_{j,t}^2}} \delta_{j,t} = \sqrt{S_{j,t}}$$ \hspace{1cm} (5)$$

$$\psi_{i,t}^h(h) = S_{i,t}^{\frac{1}{2}} A_{h,t} S_{i,t} \varepsilon_{i,t}$$ \hspace{1cm} (6)$$

Where $\delta_{j,t}$ represents the selection vector with one on the $j$th position and zero otherwise, $F_{t-1}$ is the information set until $t-1$, $\psi_{j,t}^h(h)$ represents the GIRFs of variable $j$ and $h$ represents the forecast horizon. Afterwards, we can compute the GFEVD that is interpreted as the variance share one variable has on other variables $j$. The $h$-step ahead GFEVD ($\hat{\phi}_{j,i}^h(h)$) can be calculated as follows,

$$\hat{\phi}_{j,i}^h(h) = \frac{\sum_{j=1}^{h-1} \psi_{j,t}^h(h)}{\sum_{j=1}^{N} \sum_{i=1}^{N} \psi_{j,t}^h(h)} \hspace{1cm} \sum_{j=1}^{N} \hat{\phi}_{j,i}^h(h) = 1 \hspace{1cm} \sum_{i=1}^{N} \hat{\phi}_{j,i}^h(h) = N$$ \hspace{1cm} (7)$$

Using the GFEVD, the total connectedness index can be obtained:

$$C^i_l(h) = \frac{\sum_{i,j=1}^{N} \hat{\phi}_{j,i}^h(h)}{\sum_{i,j=1}^{N} \hat{\phi}_{j,i}^h(h)} \times 100$$ \hspace{1cm} (8)$$

First, we focus on the spillovers of variable $i$ to all others $j$, representing the total directional connectedness to others and formulated by:

$$C^i_{-j,i}(h) = \frac{\sum_{j=1}^{N} \hat{\phi}_{j,i}^h(h)}{\sum_{i=1}^{N} \hat{\phi}_{j,i}^h(h)} \times 100$$ \hspace{1cm} (9)$$

Second, we compute the spillovers of all variables $j$ to variable $i$, representing the total directional connectedness from others and defined as:

$$C^i_{-j,i}(h) = \frac{\sum_{i=1}^{N} \hat{\phi}_{j,i}^h(h)}{\sum_{i=1}^{N} \hat{\phi}_{j,i}^h(h)} \times 100$$ \hspace{1cm} (10)$$
Third, we subtract the total directional connectedness to others and total directional connectedness from others to get the net total directional connectedness:

\[ C^r_{it} = C^r_{i, jdt}(h) - C^r_{i, jtd}(h) \]  \hfill (11)

If \( C^r_{it} > 0 \), it means that variable \( i \) influences the network more than being influenced by it. By contrast, if \( C^r_{it} < 0 \), it means that variable \( i \) is driven by the network.

Finally, we break down the net total directional connectedness to examine the bidirectional relationships by computing the net pairwise directional connectedness (NPDC):

\[ NPDC_{ij}(h) = \hat{\psi}_{ij}(h) - \hat{\psi}_{ji}(h) \]  \hfill (12)

If \( NPDC_{ij}(h) > 0 \), it means that variable \( i \) is driving variable \( j \), otherwise, it means that variable \( i \) is driven by variable \( j \).

Table 1. Information for the financial institutions.

<table>
<thead>
<tr>
<th>Panel A: Banks</th>
<th>Abbr.</th>
<th>Ticker code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ping An Bank Co., Ltd</td>
<td>PAB</td>
<td>000001.SZ</td>
</tr>
<tr>
<td>Bank of Ningbo</td>
<td>NBCB</td>
<td>002142.SZ</td>
</tr>
<tr>
<td>Shanghai Pudong Development Bank Co., Ltd</td>
<td>SPDB</td>
<td>600,000.SH</td>
</tr>
<tr>
<td>Hua Xia Bank Co., Limited</td>
<td>HXB</td>
<td>600,013.SH</td>
</tr>
<tr>
<td>China Minsheng Banking Corp., Ltd</td>
<td>CMSB</td>
<td>600,016.SH</td>
</tr>
<tr>
<td>China Merchants Bank Co., Ltd</td>
<td>CMB</td>
<td>600,036.SH</td>
</tr>
<tr>
<td>Bank of Nanjing</td>
<td>NJCB</td>
<td>601,009.SH</td>
</tr>
<tr>
<td>Industrial Bank</td>
<td>CIB</td>
<td>601,166.SH</td>
</tr>
<tr>
<td>Bank of Beijing</td>
<td>BOB</td>
<td>601,169.SH</td>
</tr>
<tr>
<td>Industrial and Commercial Bank of China Limited</td>
<td>ICBC</td>
<td>601,398.SH</td>
</tr>
<tr>
<td>China Construction Bank Corporation</td>
<td>CCBC</td>
<td>601,939.SH</td>
</tr>
<tr>
<td>Bank of China Limited</td>
<td>BCL</td>
<td>601,988.SH</td>
</tr>
<tr>
<td>China CITIC Bank Corporation Limited</td>
<td>CCITIC</td>
<td>601,998.SH</td>
</tr>
<tr>
<td>China Everbright Bank Co., Ltd</td>
<td>CEIB</td>
<td>601,818.SH</td>
</tr>
<tr>
<td>Bank of Communications</td>
<td>BOCOM</td>
<td>601,328.SH</td>
</tr>
<tr>
<td>Agricultural Bank of China Ltd</td>
<td>ABC</td>
<td>601,288.SH</td>
</tr>
<tr>
<td>Sichuan Western Resources Holding Co., Ltd</td>
<td>WR</td>
<td>600,139.SH</td>
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</table>

<table>
<thead>
<tr>
<th>Panel B: Securities</th>
<th>Abbr.</th>
<th>Ticker code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Northeast Securities Co., Ltd</td>
<td>NS</td>
<td>000686.SZ</td>
</tr>
<tr>
<td>Guoyuan Securities Company Limited</td>
<td>GSCL</td>
<td>000728.SZ</td>
</tr>
<tr>
<td>Sealand Securities Co., Ltd</td>
<td>SS</td>
<td>000750.SZ</td>
</tr>
<tr>
<td>GF Securities Co., Ltd</td>
<td>GFS</td>
<td>000776.SZ</td>
</tr>
<tr>
<td>China Merchants Securities Co., Ltd</td>
<td>CMSC</td>
<td>600,999.SH</td>
</tr>
<tr>
<td>Changjiang Securities Co., Ltd</td>
<td>CS</td>
<td>000783.SZ</td>
</tr>
<tr>
<td>Sinolink Securities Co., Ltd</td>
<td>SLS</td>
<td>600,109.SH</td>
</tr>
<tr>
<td>Southwest Securities Co., Ltd</td>
<td>SWS</td>
<td>600,369.SH</td>
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<td>Hantong Securities Co., Ltd</td>
<td>HS</td>
<td>600,837.SH</td>
</tr>
<tr>
<td>CITIC Securities Company Limited</td>
<td>CITIC</td>
<td>600,030.SH</td>
</tr>
<tr>
<td>Pacific Securities</td>
<td>PSC</td>
<td>601,099.SH</td>
</tr>
<tr>
<td>Industrial Securities Co., Ltd</td>
<td>CISC</td>
<td>601,377.SH</td>
</tr>
<tr>
<td>Huatai Securities Co., Ltd</td>
<td>HTSC</td>
<td>601,688.SH</td>
</tr>
<tr>
<td>Everbright Securities Co., Ltd</td>
<td>ESC</td>
<td>601,788.SH</td>
</tr>
<tr>
<td>Guangdong Golden Dragon Development Inc.</td>
<td>GGDD</td>
<td>000712.SZ</td>
</tr>
<tr>
<td>Polaris Bay Group Co., Ltd</td>
<td>PB</td>
<td>600,155.SZ</td>
</tr>
<tr>
<td>Xiangeai Securities Co., Ltd</td>
<td>XISC</td>
<td>000929.SZ</td>
</tr>
<tr>
<td>Shaanxi Securities Co., Ltd</td>
<td>SXSC</td>
<td>002500.SZ</td>
</tr>
<tr>
<td>Jingwei Textile Machinery Co., Ltd</td>
<td>JWTM</td>
<td>000666.SZ</td>
</tr>
<tr>
<td>Eastmoney Securities Co., Ltd</td>
<td>EMSC</td>
<td>300059.SZ</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel C: Insurers</th>
<th>Abbr.</th>
<th>Ticker code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Xishui Strong Year Co., Ltd</td>
<td>XSY</td>
<td>600,291.SH</td>
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<tr>
<td>China Life Insurance Company Limited</td>
<td>CLIC</td>
<td>601,629.SH</td>
</tr>
<tr>
<td>China Pacific Insurance Co., Ltd</td>
<td>CPCI</td>
<td>601,601.SH</td>
</tr>
<tr>
<td>Hubei Biocause Pharmaceutical Co., Ltd</td>
<td>HBP</td>
<td>000627.SZ</td>
</tr>
<tr>
<td>Ping An Insurance Co. of China, Ltd</td>
<td>PAI</td>
<td>601,318.SH</td>
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</table>

<table>
<thead>
<tr>
<th>Panel D: Diversified Financials</th>
<th>Abbr.</th>
<th>Ticker code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Minsheng Holdings Co., Ltd</td>
<td>MH</td>
<td>000416.SZ</td>
</tr>
<tr>
<td>Hainan Haide Industry Co., Ltd</td>
<td>HH</td>
<td>000567.SZ</td>
</tr>
<tr>
<td>Ccap Capital Company Limited</td>
<td>CCCL</td>
<td>000617.SZ</td>
</tr>
<tr>
<td>Guangzhou Yuexia Financial Holdings Group Co., Ltd</td>
<td>GYFH</td>
<td>000987.SZ</td>
</tr>
</tbody>
</table>
The fluctuation of stock prices and earnings of financial institutions is a risk contagion channel and has a spillover effect. Based on this, this paper chooses the closing price of financial institutions to represent the market performance. The daily closing prices of 62 financial institutions (Table 2), included 17 monetary and financial service institutions, 25 capital market service institutions, 5 insurance institutions, and 15 other diversified financial institutions, where the sample data ranged from 1 January 2011 to 31 December 2021. Since the start of COVID-19 on 20 January 2020, China's financial market has been severely impacted by it. After 31 December 2020, the COVID-19 vaccine developed by China was officially put into the market, which played a decisive role in controlling the epidemic and had a significant impact on investor sentiment. Therefore, the period from 20 January 2020 to 31 December 2020 is in the epidemic, and the period from 4 January 2021 to 31 December 2021 is the post-epidemic era.3

Referring to the summary statistical results, all data indices are negatively skewed. Additionally, all kurtosis values were higher than 3, indicating that all volatility and return series had a heavy tail and peak relative to a normal distribution. Both the kurtosis and skewness values were greater than three, indicating that the data is non-normally distributed, peaked and skewed. Based on the descriptive statistics, however, the data fulfilled the requirements of normality. Further, the ADF tests supported the stationarity of all series at 10% level, which confirmed that the data was stable. The Ljung Box test (calculated up to 20 lags) allowed the null hypothesis that there was no autocorrelation for all series and their squares, indicating that there were significant linear or nonlinear correlations in the samples. In addition, the ARCH-Lagrange multiplier statistics (with 10 lags) showed that all sequences exhibited volatility clustering, which supports the use of the GARCH model in this study.4

3 The division of this period is consistent with the research of Yang Zihui, Wang Shudai (2021), Fang Yi, Jia Yanyan (2021). There was no epidemic data disclosed before January 19, 2020, and the launch date of COVID-19 vaccine in China is December 31, 2020.

4 There are a large number of financial institutions in this paper, so descriptive statistical results are not shown in this paper.

3. **Static spillover analysis**

This section analyzes the risk spillover relationship among financial institutions and examined
the correlation from the static perspective (Ghulam et al., 2019).

Table 2 presents the static volatility connectedness among financial institutions. The elements on the main diagonal represent the impact from its own disturbance, while the elements on the lesser diagonal represent the directional risk spillover effect of the pairwise interaction. Among them, "NET" represents the risk net spillover effect of financial institutions to other institutions, and "TOTAL" represents the total spillover effect of the financial institutions. The off-diagonal column represents contributions to others ("TO"), and the row sums of the table represent the contributions from others ("FROM").

Table 2. Total, net, and pairwise spillovers among financial institutions

<table>
<thead>
<tr>
<th></th>
<th>Insurers</th>
<th>Securities</th>
<th>Banks</th>
<th>Diversified financials</th>
<th>FROM</th>
</tr>
</thead>
<tbody>
<tr>
<td>Insurers</td>
<td>42</td>
<td>20.4</td>
<td>20.9</td>
<td>16.7</td>
<td>58</td>
</tr>
<tr>
<td>Securities</td>
<td>19.5</td>
<td>39.3</td>
<td>14.9</td>
<td>25.6</td>
<td>60.7</td>
</tr>
<tr>
<td>Banks</td>
<td>23.8</td>
<td>17.6</td>
<td>46.4</td>
<td>11.6</td>
<td>53.6</td>
</tr>
<tr>
<td>Diversified financials</td>
<td>17.3</td>
<td>28.5</td>
<td>11.3</td>
<td>43.3</td>
<td>57</td>
</tr>
<tr>
<td>TO</td>
<td>60.6</td>
<td>66.5</td>
<td>47.1</td>
<td>55.1</td>
<td>229.4</td>
</tr>
<tr>
<td>NET</td>
<td>2.7</td>
<td>5.8</td>
<td>-6.5</td>
<td>-2</td>
<td></td>
</tr>
<tr>
<td>NPDC</td>
<td>1</td>
<td>0</td>
<td>3</td>
<td>2</td>
<td>57.3</td>
</tr>
</tbody>
</table>

Using the static volatility spillover index, Table 2 reveals that the total connectedness index reached 229.4% during the whole sample period. The main diagonal elements represent their own shock contributions. Among them, the volatility spillovers of banks to themselves reached 47.3%, indicating its strong stability. The stability may be due to that the business of the banks links with other sub-industry. The off-diagonal values represent the shock contributions from other financial institutions and thus reflect the magnitude of the risk spillovers between different financial institutions. The volatility connectedness of the financial institutions is due primarily to the impact of securities. Among them, securities with a fluctuation weight of its external output as high as 65.4% as found to have a significant impact on other financial institutions.

According to the FROM index, securities are the biggest recipient of volatility connectedness or spillovers (60.2%). The debt investors in securities easily transmit financial risk efficiently between investors through bond debt relations and spread panic quickly, which has an apparent risk spillover effect transmission on the rest of the financial institutions in the financial system. Conversely, banks are the smallest recipient of risk spillover from others. The values of the directional connectedness of securities are larger than others in the “TO” index, while the banks and diversified financials are the most miniature transmitters. As for the NET indicators in the table, securities and insurances were the net transmitters, while banks and diversified financials were the net recipients in the cryptocurrencies market. The banks and diversified financials may link closely with other financial institutions in the financial system.

Table 4. Total, net, and pairwise spillovers among financial institutions about COVID-19
Considering the impact of PHEIC such as COVID-19 on the financial system, we further analyze the spillover index results of the financial institutions in the COVID-19 and post-epidemic era. In contrast, Table 3 shows that the total spillover index reached 254.9% in the COVID-19, indicating that the overall spillover of the financial system increased under the influence of the pandemic. From the perspective of FROM, each sub-industries of financial institutions is more affected by others in the COVID-19, while each sub-industries is significantly less affected by risk spillover during the recovery period of COVID-19 (post-epidemic era). In addition, the banks have the most significant change rising to 64.4% in the COVID-19 and falling to 44.5% in the post-epidemic era. Financial institutions changed the same as the FROM index in the TO index. The greatly changing of spillover index of banks shows that China's banks is greatly affected by the COVID-19 due to monetary policy regulation and other reasons. According to the Net index in the table, the transmitter and recipient of the financial institutions remain unchanged. The banking industry is the primary recipient of risk spillover, and the securities industry is the main transmitter of risk spillover.

4. **Dynamic spillover analysis**

Using the rolling-window analysis method, we revealed the changes in the financial institutions during the sample period. The total spillover index for the volatility series is shown in Figure 2, which shows the total volatility connectedness among the financial institutions. The total spillover of financial institutions has fluctuated since 2012, and it can be seen that there were 6 climbing periods in the total spillover plot. The total volatility index of financial institutions fluctuates between 25% and 70%, indicating that the risk contagion within financial institutions is obvious, especially in the face of shocks. We analyzed these cycles based on the relevant events that may cause them, preventing the uncertain and volatile risk contagion within financial institutions. The first small cycle was in November 2013, when the total risk spillover index reached 67%. The liquidity strain of the interbank may be the reason for the climbing of total spillover index, which is linked to bond markets, stock exchanges, and gold markets. However, the PBC still maintained the current monetary policy to test the banks' ability to respond to a liquidity crisis until July 2013, when the PBC fully liberalized the interest rate liberalization.

The second period is January 2015, which may be related to the changes in banks. Since 2015,
the reform of subsidiaries of commercial banks has been continuously promoted, including China Everbright Bank, Bank of China, China Construction Bank, and Industrial Bank. At the same time, different types of banks all launched Internet products since March 2015. Besides, on January 19, 2015, the Shanghai Stock Index fell by 9.04%.

The third period was July 2015. The stock market slumped many times while the price of cryptocurrencies overgrew. The global capital market fell to the lowest level of stock market volatility and fear index forecasted volatility in more than 30 years. Chinese regulatory authorities, such as the China Securities Regulatory Commission (CSRC), issued relevant policies to improve market liquidity, stabilize abnormal fluctuations in the stock market, and gradually reduce the total spillover index.

The fourth period is January 2016. The Shanghai Stock Index fell 5.98%, while the Chinese government restarted a period of financial deleveraging to reduce the macro leverage ratio and take several measures to prevent financial risks. In 2016, the Central Economic Work Conference noted preventing financial risks, maintaining steady and rapid economic development, and damping down price rises. The 19th National Congress of the Communist Party of China called for improving the financial regulatory system to guard against systemic risks. At the 2018 Central Economic Conference, Yi Gang mentioned the remarkable results of multiple measures taken in the financial system. As a result, the risk spillover index keeps falling and hitting the bottom.

The fifth period is in 2018, when the volatility spillover index fluctuated wildly throughout the sample period. Following the fall in the previous period, the risk spillover index sharply increased by nearly 35%. The reason is related to the debt default and other credit events such as the P2P “explosion” of Internet finance in the domestic market. Many of stocks in the Shanghai Stock Exchange and Shenzhen Stock Exchange fell by the daily limit, and the three major indexes frequented continuously. The Shanghai Composite Index fell 8.14 percent, the Shenzhen Component Index fell 8.53 percent, and the Growth Enterprise Market lost 6.91 percent. In March 2018, the United States decided to impose additional punitive tariffs on imported products from China, which had a major impact on Chinese stock markets, U.S. stock market index, Thailand, Philippines, Korea, Pakistan, Indonesia, Brazil, and Canada stock markets.

The sixth period is February 2020, when COVID-19 broke out. At this time, the volatility spillover index reached its highest point, about 68%, and the Chinese overall economic environment was affected by the epidemic. Since the "lockdown" of Wuhan on January 23, all industries have stagnated because of the COVID-19, investors' panic and fear have spread, and the stock market has been volatile, which made the possibility of systemic financial risks has increased. With the epidemic entering the recovery period (post-epidemic era), the government has introduced policies to promote economic recovery. Besides, People's Bank of China has implemented a prudent monetary policy, making an appropriate balance between domestic and external demand, and maintaining reasonable and abundant liquidity. Thus, these policies reduced the actual cost of social financing, supported the development of the real economy and stimulated the vitality of market.
entities. The fluctuation of the financial market caused by economic recovery policy increases the probability of systemic risks.

The seventh period is July 2020, COVID-19 cases and deaths continue to increase during this period. In addition, the COVID-19 affected the industrial and supply chains, which increased the scale of nonperforming loans and declined asset quality, and profits of financial institutions. Besides, the Chinese government introduced a series of lockdown and quarantine policies, as well as tax and rent reduction policies aimed at economic recovery, to put people's life safety first. Constant changes in relevant policies may lead to increased volatility index and risk contagion among financial institutions. At the same time, Baoshang Bank filed for bankruptcy on August 6, 2020.

The eighth period is September 2021, with the emergence of mutated COVID-19 viruses such as Alpha, Beta, Gamma, Delta, Lambda, and Omicron. It can be seen that the risk spillover index can genuinely reflect the overall risk level of Chinese financial institutions in different periods, which can provide a certain reference for investors. The risk spillover index increases significantly in the face of abnormal shocks and decreases under adequate financial supervision. Overall, the risk spillover index can be used to describe and measure the vital point that may produce systemic financial risks. Through the spillover index, the dynamic monitoring of the financial system can be realized, and the financial system’s abnormal fluctuations can be reflected to effectively prevent systemic financial risks.

Figure 1. Total spillover index
Considering the total spillover index of financial institutions, figures 2-4 show the results of risk contributions from others, risk contributions to others, and risk net spillover effect of financial institutions to others in the whole sample period. The dynamic spillover index of financial institutions in China has changed significantly after COVID-19, with great changes in risk spillover degree and little change in the role of institutions. In the recovery period of COVID-19, the total spillover index changes in reverse from the outbreak period, indicating the impact of such public health emergencies lasts for a short time on the economy.

During the COVID-19, the spillover effect of banking and diversified service institutions increased, while the spillover effect of the securities industry decreased, and the spillover effect of insurers was volatile. Among them, the reasons may be related to the different business types of Chinese financial institutions, which would lead to the change in their spillover effects. From the perspective of the net spillover effect (FIG. 4), the securities are the net spillover of China's financial institutions, which greatly impacts the risk spillover of other sub-industries. Banks are net receivers in all the years except in the second half of 2017, due to the related-business, so they are easy to receive risk contagion. Insurers was a net receiptor except in the second half of 2017 and 2021, because of improvement of risk prevention awareness risk of investors after COVID-19. Diversified financials were net transmitters in the COVID-19, and net receipters during the COVID-19 recovery period. The change in the sample period was large because of the diversity of their own business types. In the COVID-19, investors reduced the investment decisions for safety and the prevention policy of the government, and the fall in demand increased the spillover risk to other financial institutions by diversified financials. During the recovery period, diversified financials have changed the role in the spillover effect again, with the policy of the government and the demand for investment changing repeatedly.

5. Network visualization of risk spillovers

To display the results of the net spillover network of the Chinese financial institutions intuitively, we characterize the networks graphically using several devices, including node's naming convention, node's size, and edge's direction (Yi et al., 2018). Among them, node's naming convention is short for each sub-industries of Chinese financial institutions (see Table.1). Node's size indicates the degree centrality for each sub-industries, and edge's direction represents the net spillover direction between different sub-industries (Zhang et al., 2020).
To calculate the degree centrality, which is used to determine the spillover transmitters or receivers of the cryptocurrencies, we use the complex network method to display the connectedness of the financial institutions in the sample period (see Figure 4). According to the method of Lin et al. (2021), the specific steps of constructing the networks are as follows: (1) Measuring the net spillovers between each pair in the financial institutions (2) Selecting two periods of COVID-19 as the boundary, we divided the estimated NET index into two sub-periods, in the epidemic and the post-epidemic era of COVID-19 (3) Averaging the time-varying pairwise spillover index based on each sub-period, then plotting the pairwise net spillover network of the financial institutions (See Figure 4). The greater the degree centrality of the sub-industry in the financial institution network, the more vital the systemical importance of the sub-industry in the financial institution network.

The greater the spillover effect of a sub-industry on its neighbor sub-industry in the financial institution network, the stronger the risk contagion ability of the sub-industry in the financial institution network.

First, we identified many differences in the degree centrality of each node pairwise net spillover network of the financial institutions in the sample period. The banks have the largest output-centrality, followed by diversified financials, indicating that the banking industry have the most systemic importance in the network of financial institutions. Regulators should be focused on banks, which has vital system importance and large spillover effects, the bankruptcy of the banks affect the entire financial system. In addition, diversified financials have different types of business with high system correlation, that are easy to spread the risk. However, the financial institutions to be monitored should not remain unchanged, that needs to combine various information to consider the risk spillover relations.

The main risk transmitters in the cryptocurrency market were banks, while the main transmitters have shifted to insurers (2.9), securities (2.7), insurers, and diversified financials (0.6). Besides, the securities and insurers are the main recipient in the financial institutions.

![Figure 5. Bidirectional net spillover networks in financial institutions -- based on in-degree centrality and out-degree centrality](image)

According to the network analysis of different periods of COVID-19, the spillover direction of the financial institutions’ network did not change, but the node (degree centrality) changed during the COVID-19 and the recovery period. In terms of nodes, banks and diversified financials remain systemically important institutions in different periods of COVID-19, and both banking and diversified financials become smaller during the COVID-19 and larger during the recovery period.
In terms of spillover effects from financial institutions, the risk contagion ability of banks to insurers and securities is still the strongest during the COVID-19, but the index drops to 2 and 2.2. diversified financials had the weakest risk contagion to the insurers, at 0.3. During the recovery period, the risk contagion capacity of the financial institution network increased, with the index of the banks to the insurers and securities increasing to 3.6, and the index of the diversified financials to the insurers increasing to 0.7. This indicates that in the period of COVID-19, the spillover effect of financial institutions weakened after the shock of COVID-19, but increased in the recovery period.

Figure 6. Bidirectional net spillover networks in financial institutions in the epidemic--based on in-degree centrality and out-degree centrality

Figure 7. Bidirectional net spillover networks in financial institutions in the post-epidemic era --based on in-degree centrality and out-degree centrality

6. Conclusion

Under the influence of major events such as COVID-19, investors should pay closer attention to the analysis of connectedness and risks in the financial institutions. In this study, we examined the impact of the COVID-19 pandemic among financial institutions from multiple perspectives, including measuring the effect of COVID-19 on cross-sectors linkages, analyzing the dynamic evolution of risk transmission relations and transmission paths among different sectors in financial institutions. In addition, we also explored the systemic importance nodes and structural change among the financial institutions before and after the outbreak of the COVID-19 using the complex network analysis method.

The results of this study revealed that COVID-19 had an obvious impact on the financial
institutions and significantly increased its overall risk spillover effect. The Banks and Diversified financials are easy to influence by other institutions, and the financial institutions’ net transmissions are Securities and Insurers. It was revealed that there were eight shape increasing in the different periods studied, which were affected by the pandemic and its own factors as a whole. In addition, the total volitility index reach its highest level in COVID-19. The empirical results also suggest that, and the systemic importance institutions in the network are Banks and Diversified financials.

Our findings can provide some valuable information for regulators and investors. We identify systemically important financial institutions should be focused in order to prevent risk contagion, which is one key tasks of regulators. We also find the similarity structure among networks in different sample period, which indicates that financial institutions are highly connected or systemic importance in a network should be paid attention.

Our results also can provide meaningful insights to investors and regulators. For investors, in order to diversify benefits and reduce risks when investing in China’s financial institutions, they should adjust their portfolios at different quantiles and invest in financial institutions from different sectors. For regulators, as to minimize losses and hedge risks, network topology should be given sufficient attention as a useful early warning signal. Chinese government should continue to maintain strict financial supervision and regulation, which has been effective in controlling systemic financial risks during COVID-19. It is necessary to establish an early-warning system for abnormal fluctuations and risks in financial system. By measuring the spillover network among financial institutions, we can measure and predict the systemic financial risk in Chinese financial system. The dynamic measurement of financial institutions spillover index can give early warning to financial system about some abnormal fluctuations, so as to effectively prevent systemic financial risks.
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