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A DEMAND-ORIENTED INDUSTRY-SPECIFIC VOLATILITY SPILLOVER NETWORK ANALYSIS OF CHINA'S STOCK MARKET AROUND THE OUTBREAK OF COVID-19

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ABSTRACT

Using a carefully selected industry classification standard, we divided 102 industry security indices in China's stock market into four demand-oriented sector groups and identified demand-oriented industry-specific volatility spillover networks. The demand-oriented concept is a new way in which to reconstruct the structure of the networks. Analyzing networks from a demand-oriented perspective can improve the understanding of the change in economic demand, especially when the macroeconomy is dramatically influenced by exogenous shocks, such as those due to the outbreak of COVID-19. At the beginning of the outbreak, spillover effects from industry indices of sectors meeting the investment demand to those meeting the consumption demands rose significantly in China's stock market. However, these spillover effects declined after the outbreak containment in China appeared to be effective. In addition, some service sectors, including utility, transportation and information services, have played increasingly important roles in the networks of industry-specific volatility spillovers since the COVID-19 outbreak. The efforts to contain the outbreak, led by the Chinese government, have been successful and work resumption has been organized with high efficiency. First, the risk of investment demand has therefore been controlled and eliminated relatively quickly. Second, the intensive use of non-pharmaceutical interventions (NPIs) has led to supply restrictions in services in China, which will still be a potential threat to economic recovery in the next stage.

Contribution/Originality: This is one of very few studies that has investigated the volatility spillovers in the industry-specific networks of China's stock market during the COVID-19 pandemic. The paper's primary contribution is finding the critical role that the service sectors play in the industry-specific network after the COVID-19 outbreak was contained.

1. INTRODUCTION

Frequently in the stock market, fluctuations in stock prices initially occur in companies belonging to one sector and gradually spread to other sectors. China's stock market has become the second largest in the world. Up to January 2020, 3780 companies from a variety of sectors listed their shares on China's stock market, which had a total value of more than 60.38 billion RMBs (approximately equal to 8.65 trillion US dollars). Thus, it is important for both investors and policymakers around the world to understand the complex linkage effects shown by fluctuations in the stock prices (or yields) of companies in different sectors in China's stock market.

One of the typical measurements of the linkage characteristics between different variables is the spillover effect, which can be measured by using the generalized autoregressive conditional heteroskedastic (GARCH) family of models (such as the BEKK-GARCH and DCC-GARCH models) or the variance decomposition model under the vector autoregression (VAR) framework (Diebold & Yilmaz, 2012; Jiang, Jiang, Nie, & Mo, 2019; Singh, Kumar, & Pandey, 2010).

Studies on industry-specific volatility spillover networks have highlighted the measurement of the linkage level. These studies were initially motivated by finding the arbitrage opportunities between upstream and downstream industry sectors in the supply chain. In addition, studies, such as those by Yarovaya, Brzeszczyński, and Lau (2016) and Yin, Liu, and Jin (2020), further found that volatility spillovers also exist between industry sectors without a direct input–output relationship. However, the existing literature does not answer the question of how industry-specific volatility spillover networks reflect economic demand and its changes. We believe that there are two reasons for this. First, it is more difficult to provide a proper explanation for the findings in analyses on industry-specific volatility spillover networks than those done across countries or regions. Part of the detected spillovers in the networks might match economic theory, such as the spillovers between the energy and finance sectors, or those between the transportation and consumption sectors (Gonzalez-Navarro & Quintana-Domeque, 2016; Singh, Nishant, & Kumar, 2018). However, the rest of the spillovers might not be properly explained. Second, some scholars have criticized the arbitrariness when selecting industry classification standards. Mateus, Chinthalapati, & Mateus (2017) pointed out that the industry classification standard should be cautiously selected depending on the research targets. When necessary, self-built industry indices should also be used for pursuing more meaningful numerical results and theoretical implications.

Some early studies on this topic showed that exogenous shocks to the macroeconomy of a country do not lead to fluctuations in the prices of all securities in the country at the same time (Campbell, Lettau, Malkiel, & Xu, 2001; Ewing, Forbes, & Payne, 2003; Wang, 2010). Inspired by these studies, we further considered how the demand structure influences industry-specific spillover networks. The demands of a country mainly comprise consumption, investment and export. One of the critical factors of the profit and asset price of companies is whether or not their goods or services successfully meet a part of the demand (Acemoglu & Guerrieri, 2008). The influence of exogenous shocks on economic demand should, therefore, be reflected in the structural change in the industry-specific volatility spillover networks.

To highlight the economic demand structure, we chose the industry classification standard constructed by SWS Research Co., Ltd., which is the largest securities research institute in Mainland China[1]. Using the SWS standard, we identified the GARCH-BEKK-based demand-oriented industry-specific volatility spillover networks of China's stock market. Each node in the networks represents a level 2 industry securities index in the SWS industry list. We chose the minute-per-minute return data between January 2 and March 20, 2020 for 102 SWS industry indices as the sample. In this period, the exogenous shock of the outbreak of COVID-19 dramatically changed economic demand in China.

[1] Most of the studies on industry-specific spillover network analysis of China's stock market chose the industry classification standard created by China Securities Index (CSI) Co., Ltd. (the CSI standard). However, the CSI standard cannot match all research targets. According to the CSI standard, the categories of "consumption goods" and "capital goods" are not parallel with each other. Companies supplying goods or services for consumption demands belong to the "consumer staples" or "consumer discretionary" sectors (level-1 categories). In contrast, companies meeting the investment demand cannot be classified as a sector. They can be classified only as an industry group, "capital goods" (a level-2 category), which belongs to the industrial sector. Thus, the spillover network analysis using the CSI standard cannot reflect the economic demand and its change correctly. The SWS standard divided the industry sectors into four sector groups, each of which is homogenous in meeting specific economic demand.

Recent studies have reported the influence of COVID-19 on both the macroeconomies and financial markets of different countries or regions. Some of them focused on the impact of the disease on the financial market in a single country, or the overall impact on global financial markets (Gupta & Chatterjee, 2020; Lewis, 2020; Procacci, Phelan, & Aste, 2020). Furthermore, according to Huang et al. (2020), industry-specific networks were identified based on macroeconomic data rather than data from financial markets. These studies provided us with a good incentive to design further research to illustrate how industry-specific volatility spillover networks can reflect change in economic demand.

Our study extends the literature and contributes the following:

(1) From the perspective of demand, we developed a new idea for reconstructing the structure of the industry-specific spillover network. By reorganizing the industry securities indices into demand-oriented sector groups, a better linkage between the theories of macroeconomics and the industry-specific network analysis of the financial market can therefore be obtained.

(2) We provided an early report of the structural change in the industry-specific volatility spillover networks of China's financial market around the outbreak of COVID-19. We further analyzed how the changes in this network reflected the changes in economic demand as a result of the disease.

(3) A list of new economic implications was found from the numerical results. First, during the entire study period, there were stable spillovers from the capital goods sector group to the consumption goods sector group. The spillovers from the capital goods and equipment manufacturing sector groups, which represent the demand for investment, to other sector groups rose significantly at the beginning of the COVID-19 outbreak. However, these spillovers declined approximately one month later. Second, the level of spillovers from the unclassified services sector group was continuously rising during the whole study period. This rising trend reflected that the intensive use of non-pharmaceutical interventions (NPIs) (Lai et al., 2020) in China caused supply restrictions to services and, therefore, had an overall impact on all types of demand.

The next section introduces the data selection and preprocessing strategies used, section 3 discusses the methodology, section 4 presents the empirical study of the demand-oriented industry-specific volatility spillover network analysis based on the SWS industry classification standard, section 5 presents a further discussion, and section 6 concludes the study.

2. DATA

The study period was from January 2 to March 20, 2020. Considering the size of the spread and the progress in containing COVID-19 both inside and outside China, we divided the study period into three subperiods. Period 1 is between January 2 and January 23, 2020; period 2 is between February 3 and February 28, 2020, and period 3 is between March 2 and March 20, 2020. Periods 1, 2 and 3 have 16, 20 and 15 trading days, respectively.[2]

We chose the SWS standard as the industry classification standard. According to this standard, securities in China's stock market are divided into 28 sectors, which are further divided into 104 industry groups. As shown in Table 1, the SWS standard integrated the sectors into four demand-oriented sector groups.

[2] As early as December 27, 2019, the local government of Wuhan began to report patients with "unknown pneumonia", and made public health responses to the infection. As of January 20, 2020, the Chinese government began to implement nationwide containment of COVID-19. On January 31, 2020, the World Health Organization (WHO) declared COVID-19 a public health emergency of international concern (PHEIC). To guarantee that all patients could be treated, the Chinese government covered all bills of pharmaceutical treatment via their budgets. In addition, to reduce the size of the pandemic, multiple non-pharmaceutical interventions (NPIs) were used by the Chinese government, including intercity travel restrictions, the early identification and isolation of suspected ill people and contact restriction measures. As a result, the outbreak was preliminarily contained in China by the end of February. Since March 18, 2020, the number of new patients has remained under ten per day. However, COVID-19 spread outside of China. On February 29, 2020, the WHO increased the assessment of the risk of spread to "very high" at a global level.

Table 1. Official categories of sector groups and sectors according to SWS industry classification standard.

Sector Group (Abbreviation)	Sector	The last four digits of the relative industry group (evel-2 category) indices codes
Consumption goods (Cg)	Agriculture, forestry, husbandry and fishery	1011, 1012, 1013, 1014 1015, 1016, 1017, 1018
	Household appliances	1111, 1112
	Food and beverage	1123, 1124
	Apparel and textiles	1131, 1132
	Light manufacturing	1141, 1142, 1143
	Biochemical and pharmaceuticals	1151, 1152, 1153, 1154, 1155, 1156
	Leisure Services	1211, 1212, 1213, 1214
	Commercial trade	1202, 1203, 1204, 1205
Capital goods (Kg)	Mining	1021, 1022, 1023, 1024
	Chemicals	1032, 1033, 1034, 1035, 1036, 1037
	Non-ferrous metal	1051, 1053, 1054, 1055
	Construction and decoration	1711, 1712, 1713
	Building materials	1721, 1722, 1723, 1724, 1725
	Ferrous metal	1041
Equipment manufacturing (Ke)	Machinery	1072, 1073, 1074, 1075, 1076
	Electronic components	1081, 1082, 1083, 1084, 1085
	Electrical equipment	1731, 1732, 1733, 1734
	Motor	1092, 1093, 1094, 1881
	Defense and military industry	1741, 1742, 1743, 1744
	Information facilities	1222, 1223
Unclassified services (Us)	Utilities	1161, 1162, 1163, 1164
	Transportation	1171, 1172, 1173, 1174, 1175, 1176, 1177, 1178
	Real estate	1181, 1182
	Bank	1192
	Non-bank financial services	1191, 1193, 1194
	Information services	1222, 1223
	Media	1751, 1752, 1761

Source: Wind Financial Database.
Notes 1: The conglomerates sector consists of listed companies with diversified businesses in which no single business is dominant. Although as a sector vertex in the sector-specific spillover network, the SWS conglomerates sector index belongs to none of the sector groups. 2: The codes of industry group indices (level 2 categories of industry classification system) consist of six digits in which the first two digits are "80".

As a supplement of Table 1, we listed the names and the codes of all industry group indices according to the SWS standard in the Appendix A. In addition, because the level 3 categories (industry) were not mentioned in this paper, we will refer to the industry group securities index as the "industry securities index" in the following sections.

The minute-per-minute data of the closing prices of 102 SWS industry securities indices are available from the Wind Financial Database. We calculated the log return of $P_{i,t}$, which is the price of index i at moment t, as $r_{i,t} = ln(P_{i,t}) - ln(P_{i,t-1})$. We obtained $r_i = \{r_{i,t}\}, t \in \{1,2,\cdots,T\}$ as the log return series of index i. The comprehensive descriptive statistics of the log return series of all industry securities indices in different periods can be found in the Appendix B.

3. METHODOLOGY

3.1. BEKK-GARCH-Based Volatility Spillover Network

The BEKK-GARCH model was proposed by Engle and Kroner (1995). The economic implication of the model is attractive because its parameters are able to detect the spillover effect between variables. Considering the time series $r_i = \{r_{i,t}\}, t \in \{1,2,\cdots,T\}$ and $r_j = \{r_{j,t}\}, t \in \{1,2,\cdots,T\}$, a bivariate BEKK-GARCH model is required to test the spillover effect between them. This bivariate model consists of a mean equation and a variance equation. According to Kang, Cheong, and Yoon (2013) and Lin, Wesseh Jr, and Appiah (2014), the lag order of both equations can be set as 1. The mean equation of the bivariate BEKK-GARCH model is shown in Equation 1:

$$\begin{bmatrix} r_{i,t} \\ r_{j,t} \end{bmatrix} = \begin{bmatrix} \mu_i \\ \mu_j \end{bmatrix} + \begin{bmatrix} \varphi_{ii} & \varphi_{ij} \\ \varphi_{ji} & \varphi_{jj} \end{bmatrix} \begin{bmatrix} r_{i,t-1} \\ r_{j,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{bmatrix} \tag{1}$$

where $\mu_i, \mu_j, \varphi_{ii}, \varphi_{ij}, \varphi_{ji}$ and φ_{jj} are the parameters to be estimated, and $\varepsilon_{i,t}$ and $\varepsilon_{j,t}$ are residuals. They are also called innovations, which represent the influence of the new information generated at moment t.

The variance model is shown below in Equation 2:

$$H_t = C'C + A'\varepsilon_{t-1}\varepsilon'_{t-1}A + B'H_{t-1}B \tag{2}$$

where $H_t = \begin{bmatrix} H_{ii,t} & H_{ij,t} \\ H_{ji,t} & H_{jj,t} \end{bmatrix}$ represents the conditional covariance matrix of r_i and r_j, and $\varepsilon_t = \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{bmatrix}$ is the innovation vector. $C = \begin{bmatrix} C_{ii} & 0 \\ C_{ij} & C_{jj} \end{bmatrix}$, $\mathrm{A} = \begin{bmatrix} a_{ii} & a_{ij} \\ a_{ji} & a_{jj} \end{bmatrix}$ and $\mathrm{B} = \begin{bmatrix} b_{ii} & b_{ij} \\ b_{ji} & b_{jj} \end{bmatrix}$ are the parameters.

To detect the volatility spillovers between r_i and r_j, the following hypotheses were tested according to Equation 3 and Equation 4.

$$H_0: a_{ij} = a_{ji} = b_{ij} = b_{ji} = 0 \tag{3}$$

$$\mathrm{H}_1: a_{ij} \neq 0 \; or \; a_{ji} \neq 0 \; or \; b_{ij} \neq 0 \; or \; b_{ji} \neq 0, \tag{4}$$

where H_0 is the null hypothesis and H_1 is the alternative hypothesis. By convention, we reject the null hypothesis at a 90% confidence level. If the null hypothesis is rejected, it means that there are spillovers between r_i and r_j. Specifically, the direction of the spillover effect is from r_i to r_j when $a_{ij} \neq 0$ or $b_{ij} \neq 0$. Otherwise, the direction is from r_j to r_i when $a_{ji} \neq 0$ or $b_{ji} \neq 0$.

To test volatility spillovers between multiple variables, a set of bivariate BEKK-GARCH models is required. After all testing has been completed, we can identify the BEKK-GARCH-based volatility spillover networks. Let $Net(V,E)$ represent the industry-specific securities index volatility spillover networks. The set $V = \{v_1, v_2, \cdots, v_N\}$ represents the vertices, also called nodes, of industry securities indices. Each of the nodes v_i is characterized by a log return time series r_i. The set E represents the edges of the networks. For $\forall v_i, v_j \in V$, the edges from v_i to v_j satisfy the indicator function e_{ij}, which is shown in Equation 5:

$$e_{ij} = \begin{cases} 1 & if \; i \neq j \; and \; there \; is \; volatility \; spillover \; from \; r_i \; to \; r_j \\ 0 & otherwise \end{cases} \tag{5}$$

We then considered the weight of e_{ij}. By referencing Liu et al. (2017) and Feng et al. (2018) we calculated the weight of the edges according to Equation 6 and Equation 7:

$$w_{ij} = |a_{ij}| + |b_{ij}| \tag{6}$$

$$w_{ji} = |a_{ji}| + |b_{ji}| \tag{7}$$

where the weights of e_{ij} and e_{ji} are represented by w_{ij} and w_{ji}, respectively. Weighted and directed BEKK-GARCH-based volatility spillover networks have now been identified. The intensity of the edge e_{ij} can be calculated as $s_{ij} = e_{ij}w_{ij}$.

3.2. Node Importance Ranking Indicators

3.2.1. Connectivity and Relative Influence

The connectivity indicators consist of O_i and I_i, which represent the total intensity of outward spillovers from v_i and the total intensity of inward spillovers to v_i, respectively. O_i and I_i were calculated according to Equation 8 and Equation 9:

$$O_i = \sum_{j=1, j\neq i}^{N} s_{ij} \tag{8}$$

$$I_i = \sum_{j=1, j\neq i}^{N} s_{ji} \tag{9}$$

Both O_i and I_i are absolute indicators. The relative influence of v_i was calculated according to Equation 10:

$$ri_i = \begin{cases} \dfrac{O_i - I_i}{O_i + I_i} & , otherwise \\ 0 & , if\ O_i + I_i = 0 \end{cases} \tag{10}$$

When dividing the nodes into groups, additional indicators were required to assess the importance of the groups according to Billio, Getmansky, Lo, and Pelizzon (2012). The outward spillover effect from the nodes in one group to those in other groups can be defined as "total out to other" (TOTO). Similarly, the inward spillover to one group from other groups can be defined as "total in from other" (TIFO). The TOTO and TIFO are shown in Equation 11 and Equation 12:

$$TOTO_i = \sum_{j=1}^{N-N_m} s_{ij}, v_j \in V \setminus V_m \tag{11}$$

$$TIFO_i = \sum_{j=1}^{N-N_m} s_{ji}, v_j \in V \setminus V_m \tag{12}$$

where v_i belongs to subset $V_m = \{v_i | i \in m\}$, which includes N_m nodes. Let $V_m, V_n \subset V$ satisfy $V_m = \{v_i | i \in m\}$ and $V_n = \{v_j | j \in n\}$. We calculated the sector influence indicator according to Equation 13:

$$SI_{mn} = \frac{1}{N_m N_n} \sum_{i \in m} \sum_{j \in n} s_{ij} \tag{13}$$

The higher the value of SI_{mn} is, the more intensive the spillover is from subset V_m to subset V_n.

3.2.2. Weighted K-Shell Decomposition

In addition to the number of neighbors, the location of a node in the network is also critical for the assessment of its importance. Kitsak et al. (2010), therefore, proposed k-shell decomposition to evaluate the locational importance of the nodes. K-shell decomposition is the method that reshapes the networks into a layered structure according to their connectivity patterns. For an unweighted network $\mathrm{N}_0 = Net(V_0, \mathrm{E}_0)$, the layer L of N_0 is a subset of nodes, each of which has only one neighbor. We assigned the layer an integer label L_1 and removed it from N_0. We then obtain a new network $\mathrm{N}_1 = Net(V_1, \mathrm{E}_1)$. Similarly, we identified the layer of the network N_{n-1}, assigned the layer a label L_n and removed it from the network. After repeating the step K times, each of the nodes in the original network N_0 can be assigned to one of the layers.

Vanilla k-shell decomposition fails to consider the intensity of connections, thus it cannot rank the nodes for weighted networks. Garas, Schweitzer, and Havlin (2012) extended vanilla k-shell decomposition to weighted k-shell decomposition. The alternative measure for node degree is shown in Equation 14.

$$wk_i = [k_i^{\alpha} O_i^{\beta}]^{\frac{1}{\alpha+\beta}} \tag{14}$$

where k_i represents the number of neighbors connected with v_i, and O_i is defined in Equation 8. According to Garas et al. (2012), the parameters can be set as $\alpha = \beta = 1$. Note that wk_i is not an integer value. Therefore, we should first divide all the weights of edges in N_0 by their minimum value and discretize the resulting weights by rounding to their closest integer. Then, we obtain $\mathrm{N}_0' = Net(V_0, \mathrm{E}_0')$, in which the minimum value of the weights equal to 1. Each step of the weighted k-shell decomposition consists of the following: first, normalize N_n to N_n', second, identify layer $k = n + 1$, and third, remove the layer from N_n, and obtain N_{n+1}.

3.2.3. Betweenness Centrality

Betweenness centrality is based on the shortest distances between nodes (Opsahl, Agneessens, & Skvoretz, 2010). For weighted directed networks, the definition of the shortest distance from v_i to v_j is shown in Equation 15:

$$d_{ij}^{\alpha} = \min_{D_{ij}}\{(s_{id_1}^{-\alpha} + s_{d_1 d_2}^{-\alpha} + \cdots + s_{d_k j}^{-\alpha}), s_{ij}^{-\alpha}\} \tag{15}$$

where $D_{ij} = \{v_{d_1} v_{d_2}, \cdots, v_{d_k}\}, 1 \le k \le N - 2$ represents a set of arbitrary intermediate nodes of the spillover paths from v_i to v_j. The set of the intermediate nodes of the shortest path can therefore be defined as D_{ij}^*. If $d_{ij}^{\alpha} = s_{ij}^{-\alpha}$, then there are no intermediate nodes in the shortest path from v_i to v_j, and $D_{ij}^* = \emptyset$. For unweighted networks, the parameter α simply equals zero. For weighted networks, the value of α depends on the relationship between the link intensity between the nodes and their distance. In the weighted and directed spillover networks of financial markets, the higher link intensity between the nodes means a shorter distance. The value of α should be positive. If there are more intermediate nodes in the spillover path between two nodes, then their distance is longer. α is supposed to be less than 1, so with a comprehensive consideration, we take $\alpha = 0.5$

We can easily define the betweenness and the closeness based on the definition of the shortest distance d_{ij}^{α}. We call the weighted betweenness centrality of v_i.the WBC_i. The WBC_i represents the proportion of shortest paths from v_j to v_k, which includes v_i as an intermediate node, it can be calculated by Equation 16.

$$WBC_i = \sum_{i \neq j \neq k} \frac{g_{jk}(i)}{g_{jk}} \qquad (16)$$

where g_{jk} is the number of different D_{jk}^{*}, and $g_{jk}(i)$ is the number of D_{jk}^{*} including v_i as an intermediate node.

3.3. Earth Mover's Distance (EMD)

None of the indicators introduced in Section 3.2 highlights measuring the distributional change in the spillover intensity. Therefore, we introduce the EMD to consider the intensity distribution change in spillovers across different groups. The EMD is a cross-bin distance that is defined as the minimal cost that must be paid to transform one histogram into another (Rubner, Tomasi, & Guibas, 2000). An intensity distribution of spillovers can be represented by countable clusters. Each cluster is represented by its mean and by the fraction of the distribution that belongs to that cluster. We refer to such a representation as the signature of the distribution. Then, the distributional change in spillover intensity between periods 1 and 2 can be formalized and solved as a transportation problem. We transformed the distribution of link strength in periods 1 and 2 into signatures $\mathcal{S}_1$ and $\mathcal{S}_2$, respectively, according to Equation 17:

$$\begin{cases} \mathcal{S}_1 = \{(S_{11}, p_{S_{11}}), (S_{12}, p_{S_{12}}), \cdots, (S_{1m}, p_{S_{1m}})\} \\ \mathcal{S}_2 = \{(S_{21}, p_{S_{21}}), (S_{22}, p_{S_{22}}), \cdots, (S_{2n}, p_{S_{2n}})\} \end{cases} \qquad (17)$$

where the intensity distribution of the spillovers in periods 1 and 2 are discretized into m and n clusters. S_{1i} and S_{2j} represent the means of the ith cluster in period 1 and the jth cluster in period 2, respectively. Both S_{1i} and S_{2j} are one-dimensional real values, and we defined the ground distance between the ith cluster in period 1 and the jth cluster in period 2 as $\mathrm{d_{ij}} = |S_{1i} - S_{2j}|$.The p_x represents the weight of cluster x. In addition, p_x

naturally satisfies $\sum_{i=1}^{m} p_{S_{1i}} = \sum_{j=1}^{n} p_{S_{2j}} = 1$. The calculation of the EMD can be transformed into the optimization of a transporting problem, which can be solved via the Hungarian method.

4. DEMAND-ORIENTED INDUSTRY-SPECIFIC VOLATILITY SPILLOVER NETWORK ANALYSIS

4.1 Network before the COVID-19 Outbreak

Table 2 reports the summary of the nodes in period 1 by group. The Kg group is a significant volatility supplier in the network. The median of O_i and that of $TOTO_i$ of the nodes in the Kg group are 6.71 and 5.39, which are much higher than those of other groups. The indicator $\sum TOTO/\sum O$ measures the proportion that outward spillovers from one sector group to other groups accounts for in its total spillovers. The unclassified services group (Us) has the highest value of $\sum TOTO/\sum O$, which is 78.55%. The medians of I_i and $TIFO_i$ of the Ke group are 5.67 and 4.48, respectively. Meanwhile, the value of $\sum TIFO/\sum I$ of this group is also the highest, which is 78.58% of its total I_i. The Kg group is also the only one with a positive median of ri_i (0.09). Those of the other three groups are all negative values, in which the lowest value (-0.15) belongs to the Cg group. The median of WBC_i of the Kg group is 39, which is also much higher than the other group counterparts. The median of WBC_i of the Us group is 16, which is the lowest value. It means that many intensive spillover paths go through the Kg group, while few of them go through the Us group.

Table 2. Medians for indicators of the nodes by sector group in period 1 (before the COVID-19 outbreak).

Sector group	O	TOTO	I	TIFO	Ri	WBC
Ke	4.50	3.54	5.67	4.48	-0.09	17.5
Cg	4.54	2.56	5.21	3.84	-0.15	21
Kg	6.71	5.39	5.50	3.69	0.09	39
Us	4.55	3.81	4.61	3.77	-0.05	16

Table 3 reports the intergroup spillovers of the network in period 1. We can find the significant asymmetry in the spillover between the Kg and Cg groups. Both the gross and net spillovers from Kg to Cg are the highest among all gross and net intergroup spillovers, which are 49.02 and 16.22. In addition, the net spillover from Kg to Ke is 14.8. Relatively, there is only slight asymmetry in the rest of spillovers. The net spillover from Cg to Ke is much weaker than that from Kg to Cg. Thus, integrating the Kg and Ke groups as a whole sector group meeting the investment demand has a net spillover to the Cg group.

In period 1, the Kg group is a main spillover contributor from all perspectives. The outward spillovers from Kg to other groups account for 23.2% of total spillovers in the network. In contrast, the Cg group is the main receiver of spillovers, which receives 22.3% of the total spillovers. The Ke group also receives 20.3% of the total spillovers, which is only slightly lower than that of the Cg group. In addition, the other three groups have net spillovers to the Ke group.

Table 3. Cross-sector group analysis of the volatility spillovers in period 1 (before the COVID-19 outbreak).

From/to	Intensity of spillovers					No. of direct spillover paths				
	Ke	Cg	Kg	Us	Total	Ke	Cg	Kg	Us	Total
Ke	30.16	36.73	26.05	21.04	537.55	223	307	207	222	4308
Cg	40.64	43.24	32.80	30.79		295	374	268	268	
Kg	40.81	49.02	37.67	34.62		284	372	247	245	
Us	27.74	34.50	27.19	24.54		217	292	202	198	

4.2. Network at the Beginning of the COVID-19 Outbreak

Table 4 reports the summary of the nodes in period 2 by group. The median of O_i and that of $TOTO_i$ of the Kg group are 8.81 and 6.39, respectively, which are even higher than those in period 1. The Kg group also has the highest value of $\sum TOTO/\sum O$, which is 76.21%. The median of O_i and that of $TOTO_i$ of the Us group are 6.15 and 4.46, respectively, which increased the most significantly compared to those in period 1. The median of I_i and that of $TIFO_i$ of the Ke group are the highest, which are 8.81 and 6.39, respectively. The median of I_i and that of $TIFO_i$ of the Cg group are 5.58 and 4.65, respectively. Moreover, the value of $\sum TIFO/\sum I$ of this group is also the highest and exceeds 80%. The highest median of ri_i is that of the Kg group, which is 0.2. The lowest value is that of the Cg group, which is -0.31. In period 2, the difference in ri_i among sector groups enlarged compared with that in period 1. The median of WBC_i of the Kg group is 33, which is still the highest. However, the median of WBC_i of the Us group is 27, which increased rapidly. This means that the centrality of nodes in the Us group becomes much higher.

Table 4. Medians for indicators of the nodes by sector group in period 2 (at the beginning of the COVID-19 outbreak).

Sector Group	O	TOTO	I	TIFO	Ri	WBC
Ke	5.19	3.96	6.74	4.71	-0.13	18
Cg	3.61	2.14	5.58	4.65	-0.31	8
Kg	8.81	6.39	5.58	3.38	0.20	33
Us	6.15	4.46	5.48	4.37	-0.06	27

Table 5 reports the intergroup spillovers of the network in period 2. We can see that the total spillover intensity and the number of spillover paths in period 2 are significantly higher than those in period 1. This means that the outbreak of COVID-19 intensified the overall spillovers in China's stock market. The gross and net outward spillovers from Kg to Cg are 61.37 and 36.32, respectively, which account for a higher proportion of total spillovers than those in period 1. Specifically, the proportion of the gross spillover from Kg to Cg increased from 9.1% to 9.5% of the total spillovers of the network. The proportion of the net spillover increased even more rapidly from 3.0% to 5.6%. In addition, the Ke and Kg groups, as an integral whole, still have a net spillover effect on the Cg group.

In period 2, the outward spillovers from Kg to other groups account for 24.0% of the total spillovers of the network. The Cg group received 24.3% of the total spillovers. In addition, the other three groups have net outward spillovers to the Cg group, including the Ke group. Therefore, Kg and Cg can be viewed as the major contributor and receiver, respectively, of the spillovers in period 2.

Table 5. Cross-sector group analysis of the volatility spillovers in period 2 (at the beginning of the COVID-19 outbreak).

From/to	Intensity of spillovers					No. of spillover paths				
	Ke	Cg	Kg	Us	Total	Ke	Cg	Kg	Us	Total
Ke	42.48	46.01	31.08	36.65	646.31	277	348	230	234	4537
Cg	36.04	35.98	25.05	28.79		267	328	261	252	
Kg	47.08	61.37	48.84	46.91		301	403	273	275	
Us	38.09	49.51	33.26	39.17		214	313	222	245	

4.3. Network after Preliminary Containment of Covid-19

Table 6 reports the summary of the nodes in period 3 by group. Instead of the Kg group, the Us group has the highest outward spillover effect in period 3. The median of O_i and that of $TOTO_i$ of the Us group are 5.37 and 4.43. The Us group also has the highest $\sum TOTO/\sum O$ value, which is 76.21%. The median of I_i of the Us group is the highest, which is 5.76. However, the $\sum TIFO/\sum I$ value of the Us group is not relatively high. This reveals that in period 3, the intragroup spillovers between the nodes in the Us group increased significantly. The Ke group still has the highest median of $TIFO_i$ (4.18). Moreover, the $\sum TIFO/\sum I$ value of group Ke is 78.41%. The Kg group has the highest median of ri_i (0.05), which is still the only positive value. The lowest value belongs to the Cg group, which is -0.18. In period 3, the gap of ri_i between different sector groups became narrower than in period 2. The Us group, instead of the Kg group, became the group with the highest median of WBC_i, the value of which is 28. In addition, the median of WBC_i of the Kg group is 27, which is only slightly lower than that of the Us group.

Table 6. Medians for indicators of the nodes by sector group in period 3 (after COVID-19 is preliminarily contained).

Sector group	O	TOTO	I	TIFO	Ri	WBC
Ke	4.70	3.76	5.42	4.18	-0.12	25
Cg	3.95	2.52	5.46	3.82	-0.18	9
Kg	5.19	4.22	5.58	4.10	0.05	27
Us	5.37	4.33	5.76	3.96	-0.01	28

Table 7 reports the intergroup spillovers of the network in period 3. Both the total spillover intensity and the number of spillover paths in period 3 are less than those in period 2. The most significant difference between the intergroup spillovers in period 3 and those in periods 1 and 2 is the occurrence of the net outward spillover from the Us group to the Kg group. The Us group, therefore, has the net outward spillovers to other three groups. In addition, the Ke and Kg groups, as an integral whole, still have the net spillover to the Cg group.

In period 3, the outward spillovers from the Us group account for 20.4% of the total spillovers of the network. The inward spillovers received by the Cg group accounted for 21.9% of the total spillovers. Therefore, the Us and Cg groups were the major contributor and receiver, respectively, of the spillovers in period 3.

Table 7. Cross-sector group analysis of the volatility spillovers in period 3 (after COVID-19 is preliminarily contained).

From/to	Intensity of spillovers					No. of spillover paths				
	Ke	Cg	Kg	Us	Total	Ke	Cg	Kg	Us	Total
Ke	30.36	34.33	28.36	27.42	566.29	209	283	220	229	4254
Cg	39.40	47.55	35.03	32.77		278	373	261	283	
Kg	35.40	41.61	33.25	32.19		250	326	232	253	
Us	32.77	48.30	34.61	32.95		211	305	206	220	

In conclusion, there are both stable patterns and significant changes in the demand-oriented industry-specific volatility spillover networks of China's stock market during the study period. First, viewing the Kg and Ke sector groups as an integral whole, they maintained significant net spillovers to the Cg group. Such spillovers were relatively stronger in period 2 than in the other two periods. Second, the Kg group always had a net outward spillover to the Ke group. Furthermore, the importance of the Us group increased and finally became the major contributor of the spillovers in period 3. Figure 2 depicts the simplified spillover paths of networks in different periods by sector group.

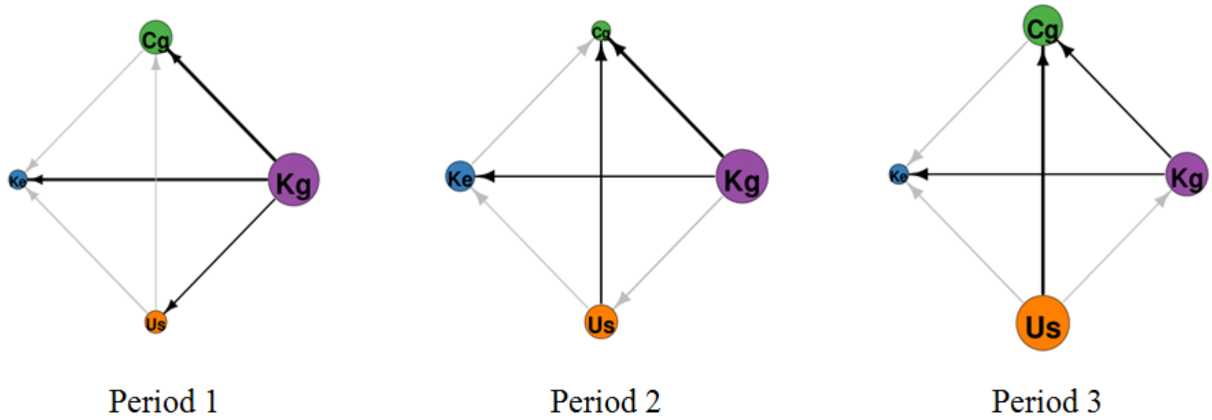

Figure 1. Demand-oriented industry-specific volatility spillover networks in different periods (net effect by sector group).
Notes: The size of each node represents the total spillover effects from this sector group to others. The width and direction of each arrow represent the strength and direction of net spillover effect between the relevant pairs of sector groups, respectively. The black arrows in each subfigure represent the major paths in each period obtained through the maximum spanning tree method.

According to Figure 1, the spillover paths from Kg to Cg and Ke were stable in all periods. The outbreak of COVID-19 led to an increasing rise in the importance of the spillover paths from the Us group to other groups. In particular, the path from Us to Cg became one of the major paths of the spillover networks of China's stock market after the outbreak.

The findings of this section have inspiring economic implications. First, some studies, such as Justiniano, Primiceri, and Tambalotti (2010), proved that fluctuations in investment demand caused by exogenous factors are the main cause of fluctuations in China's economic demand. Our numerical findings further show that the structural change in volatility spillover networks of China's stock market can reflect the critical role that investment demand plays in the fluctuation of China's economic demand since the outbreak of COVID-19. On the one hand, the Kg and Ke groups, as an integral whole, are the stable spillover contributors to the Cg group in the networks. On the other hand, the outward spillover effect from the Kg and Ke groups to the Cg group rapidly rose at the beginning of the COVID-19 outbreak. After the outbreak was preliminarily contained, these spillovers significantly fell. One of the main types of damage caused by COVID-19 was the nationwide closure and idling of plants in all trades, which has undisputedly had an enormous impact on investment demand in China. The increased uncertainty of investment demand led to the fluctuation in stock prices of securities in the industry sectors, which supplies goods or services to meet the investment demand. Therefore, regarding the change in spillovers from the Ke and Kg sector groups to the Cg group provides empirical evidence, from the perspective of the financial market, for the economic theories proposed in literature by Greenwood, Hercowitz, and Krusell (2000).

Second, the increasingly rising importance of the Us sector group in spillover networks reveals the occurrence of supply restrictions on the service industry caused by the implementation of NPIs. To contain COVID-19, the Chinese government implemented immediate NPIs nationwide. The majority of businesses in the service sector were forced to shut down, and a large percentage of transportation services in China had to idle, despite the enormous freight and passenger traffic demands. The uncertainty of COVID-19 transformed into the uncertainty of the operational environment of the companies in the service sector and, consequently, their asset prices. According to Xu and Zhang (2020), service supply restrictions will lead to an imbalance between supply and demand and will negatively affect economic growth. As a result, companies in the service sector contribute more volatility spillovers to those in other sectors. When overseas market demand is strong, a country is still able to achieve high economic growth under the condition of service supply restrictions. However, once the overseas market demand becomes insufficient, service supply restrictions will seriously damage the economy. As introduced in section 2.1, COVID-19 began to spread outside China in period 3. As a global pandemic, COVID-19 will surely lead to insufficient overseas demand for Chinese products. As a result, the importance of the Us group in the networks in period 3 is even higher than in period 2. In addition, according to Herrendorf and Fang (2019), to compare the period in which developed countries were at a similar stage of development as China is currently, there is severe supply restriction on most service industries currently in China. Service supply restriction is an overall problem rather than a structural problem in the Chinese economy. The outbreak of COVID-19 was only an exogenous shock that intensified the problem. Therefore, we believe that our findings are still representative, although not all service industry sectors are classified as members in the Us group according to the SWS standard.

5. FURTHER DISCUSSIONS

We further discussed the demand-oriented industry-specific volatility spillover networks of China's stock market from three aspects. First, we calculated the earth mover's distance (EMD) of the distributions of the spillover intensity of both inter- and intra-sector groups in different periods. Second, defining the major spillover paths as those with the top 20% highest intensity among a set of paths, we discussed the major spillover paths between different sector groups and their changes in different periods. Third, from various perspectives, we selected the systemically important nodes of the networks in different periods.

5.1. EMDs Between Spillover Intensity Distributions in Different Periods

Figure 2 depicts the intensity distributions of the spillovers between sector groups. Intensity distributions of the spillovers, both intergroup and intragroup, are right-skewed. Few spillover paths have high intensity. Most of the subfigures show that the intensity distributions of spillovers in period 1 are similar to their counterparts in period 3. The intensity distributions in period 2, in contrast, are significantly different from those in periods 1 and 3. This reveals that in period 2, the industry-specific volatility spillover network of China's stock market has significant structural changes. As an exception, the intensity distribution of the intragroup spillover paths of the Us group, and of intergroup spillover paths between the Us and Cg groups in period 2, are more similar to their counterparts in period 3, rather than to those in period 1. This exception is also consistent with the findings in section 4 and proves that COVID-19 had a more long-lasting impact on the service sector than on other sectors.

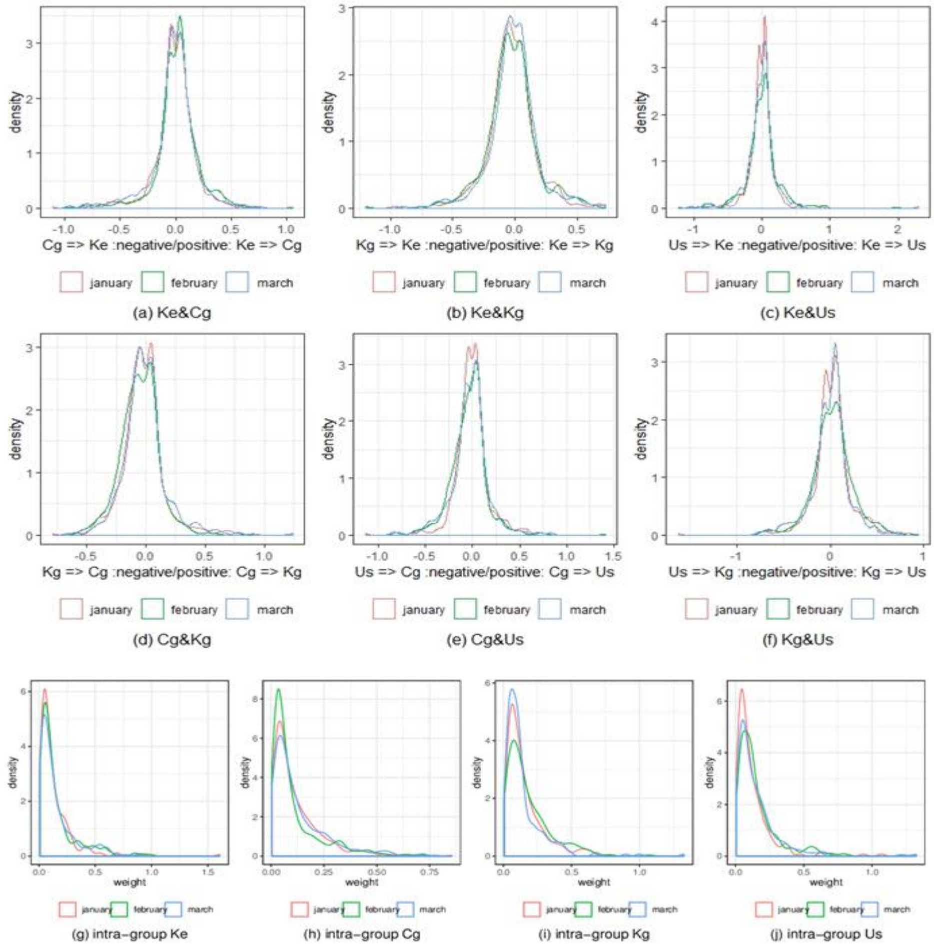

Figure 2. Empirical probability density functions of spillover intensity in different periods.

Notes: From subfigure (a) to subfigure (f), to distinguish the spillover paths in one direction to another, we processed the data further following the rule called "sector group B=>sector group A: negative/positive: sector group A=>sector group B". Following this rule, when drawing the PDFs, we took the original value of the intensity of the spillover paths from sector group A to sector group B. Otherwise, we took the opposite number of the intensity of the spillover paths from sector group B to sector group A.

Table 8 shows the EMDs between spillover intensity distributions in different periods. Between periods 1 and 2, most of the high EMDs were connected with the distribution changes in spillovers between the Us group and other groups. Specifically, the EMD of the change in the intensity distribution of spillovers from Ke to Us is 6.34%, and those from the Us group to the Ke and Cg groups are 5.11% and 4.38%, respectively. Between periods 2 and 3, most of the high EMDs were connected with the distribution changes in spillovers between the Kg group and other groups. Specifically, according to the EMD, the intensity distribution of the intragroup spillovers of the Kg group changed by 4.43%. The EMD of the change in the intensity distribution of spillovers from Kg to Us and those from Cg to Kg are 4.31% and 3.71%, respectively.

Table 8. EMDs between the intensity distributions of spillovers in different periods (%).

From\to	Period 1 vs. Period 2				Period 2 vs. Period 3			
	Ke	Cg	Kg	Us	Ke	Cg	Kg	Us
Ke	2.25	1.24	1.21	6.34	0.95	1.17	0.92	4.05
Cg	1.09	1.39	2.43	1.37	1.56	1.70	3.71	1.01
Kg	1.47	2.08	2.73	3.00	2.05	2.41	4.43	4.31
Us	5.11	4.38	2.37	3.70	2.53	1.39	1.90	1.40

The analysis in this section is a meaningful supplement for the analysis based on the sector influence indicator in section 4. From period 1 to period 2, the Us group is the sector group of which the spillover effect strength distribution had the most significant change. It revealed that, at the beginning of the outbreak of COVID-19, the nationwide implementation of NPIs is reflected immediately in the distributional characteristics of the spillover networks of China's stock market. The significant distributional change in the spillover strength concerning the Kg group from period 2 to period 3 also shows that the risk for investment demand destruction has been controlled to some extent. This is mainly due to the successful containment of COVID-19 and the resumption of work that is strongly supported by both the central and local governments of China. This means that the influence of the pandemic on the investment demand fell rapidly after the pandemic was contained in China, while the influence on service sectors was long-lasting.

5.2. Systematically Important Nodes in the Spillover Network

We selected the systematically important nodes in the volatility spillover networks in different periods from various perspectives.

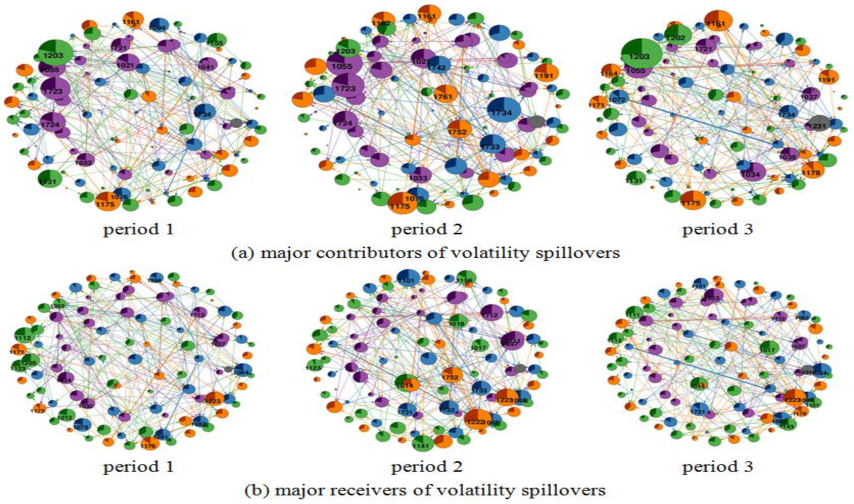

Figure 3. Major spillover effect contributors and receivers in different periods (classified by sector group).

Notes: 1. The node size of v_i is positively correlated to O_i(in subfigure (a)) or to I_i (in subfigure (b)). 2. The blue, green, purple and oranges nodes represent vertices of industry indices belonging to the Ke, Cg, Kg and Us sector groups, respectively. The conglomerates industry securities index (801231) is marked as a grey node. 3. The nodes are shown as pie charts. The proportion of the part with a lighter color in the pie chart accounts for v_i equals $TOTO_i/O_i$(in subfigure (a)) or $TIFO_i/I_i$ (in subfigure (b)). 4. The widths of edges are positively correlated with their intensity. The colors of edges are consistent with the color of nodes where they are effluent. 5. Only edges with the top 5% highest intensity of volatility spillovers are shown in each subfigure. 6. The industry securities index names corresponding with the 4-digit codes can be found in the appendix.

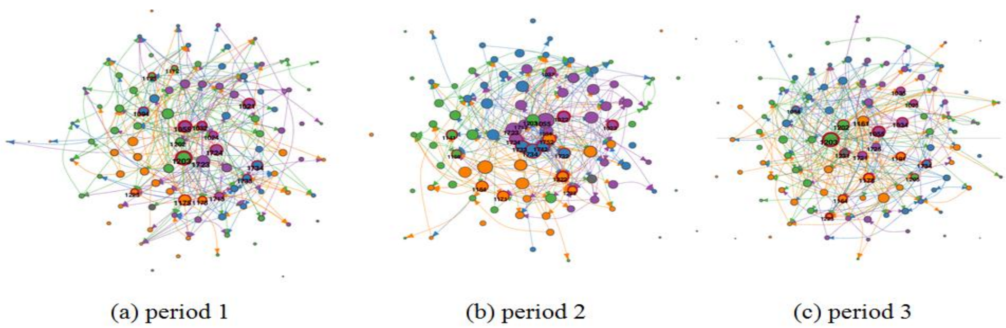

Figure 4. The centrality and k-shell decomposition structure of the nodes in different periods.

Notes: 1. The node size of v_i is positively correlated to O_i. 2. The blue, green, purple and oranges nodes represent vertices of industry indices in the Ke, Cg, Kg and Us groups, respectively. The conglomerates industry securities index (801231) is marked as a grey node. 3. The locations of the nodes depend on their k-shell level. 4. The nodes with red rings represent industry indices with the top 15 highest WBC in the networks. 5. The industry index names corresponding with the 4-digit codes can be found in the appendix.

According to Figure 3 (a), nodes in the commerce and trading sector (1202 and 1203), the construction sector (1721, 1723 and 1724), the utility sector (1161) and the transportation services sector (1175 and 1178) were the main contributors of the spillovers in all periods. Compared to period 1, a larger number of nodes in the Ke and Us groups were the main spillover contributors of the network in period 2. Compared to period 2, a larger number of nodes in the Cg and Us groups were the main spillover contributors of the network in period 3. According to Figure 3 (b), a list of nodes in the Cg group (1014, 1017, 1111, 1112, 1212, 1123, 1141, 1143 and 1156) and in the Us group (1171, 1176, 1123, 1223 and 1752) were the main spillover receivers of the network during the whole study period. After period 2, a larger number of nodes in the Kg (1712, 1037 and 1053) and Ke (1731, 1732, 1733, 1101 and 1084) groups were identified as the main spillover contributors of the network.

According to Figure 4, compared to the network in period 1, in period 2, a larger number of nodes in the Kg and Ke groups had a relatively higher betweenness centrality and k-shell level. However, in the network in period 3, a larger number of nodes in the Us group became the center of the networks. In conclusion, the analysis in section 5 further validates the main result in section 4. The spillovers from the Kg and Ke sector groups, as an integral whole, rose in period 2 and fell in period 3; the change in the spillovers from the Cg group is in contrast. Regarding the spillovers from sectors meeting the consumption demand of other sectors in China's stock market, our findings are consistent with those in the literature of Yang, Chen, and Zhang (2020) (in Chinese). However, we further illustrated how spillover networks of China's stock market reflected the relative rise and fall of the uncertainty of investment demand and consumption demand in China during the spread of COVID-19. Yang et al. (2020) also proposed that the service industry, which has suffered due to the pandemic, is a potential threat to economic recovery in China. In addition, Huang et al. (2020) found that more difficulties would be faced by industry sectors relying on transportation services during economic recovery. Based on the spillover networks of the stock market, our findings provide evidence for these studies.

6. CONCLUSIONS

According to our empirical analysis, first, the Ke and Kg sector groups, as a whole, had stable net spillovers to the Cg sector group in all of three different periods during the breakout of COVID-19. Second, the net spillovers from the Ke and Kg groups to the Cg group rose in period 2 but fell in period 3. Third, as of period 2, the importance of the Us sector group became increasingly higher. The Us group finally played the main contributor to the spillover network of China's stock market in period 3. We conducted further discussions from various perspectives, and all discussions validated our main result. We emphasize the need to discuss the demand change in a country. Our findings also have meaningful insights regarding economic recovery in the context of containing the spread of COVID-19. The investment demand in China suffered more than the consumption demand from the exogenous shock of COVID-19 at the beginning of the outbreak. However, when the pandemic was contained, the risk in investment demand in China was also controlled to some extent. The increasingly critical role that the Us sector group began to play revealed that the supply restriction in services is still a long-lasting threat to the next stage of Chinese economic recovery, especially under the condition that foreign demand is destroyed by COVID-19. We believe that NPIs are necessary for all countries and regions suffering from COVID-19. Thus, being aware of the overall influence of the service sector is critical for investors and policymakers globally.

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Appendix-A. SWS Industry securities index names corresponding with their codes.

Codes	Index names	Codes	Index names
801011	Forestry	801155	Chinese medicine
801012	Agricultural Products	801156	Health Care Service
801013	Agricultural Conglomerates	801161	electric Utilities
801014	Feed Processing	801162	Environmental Facilities & Service
801015	Fishery	801163	Gas Utilities
801016	Farming	801164	Water Utilities
801017	Husbandry	801171	Marine Ports & Service
801018	Animal Health	801172	public transit
801021	Coal Mining	801173	Airlines
801022	other Mining	801174	Airport service
801023	Oil & Gas Drilling	801175	Highways
801024	Mining Equipment & Services	801176	Marine
801032	chemical fiber	801177	Railroads
801033	Chemical materials	801178	Trucking
801034	chemical products	801181	Real Estate Management & Development
801035	Petrochemical Industry	801182	Park Exploitation
801036	Plastic	801191	Diversified Financial Service
801037	Rubber	801192	Banks
801041	Steel	801193	Capital Markets
801051	Metal New materials	801194	Insurance
801053	Gold	801202	Trading

801054	Precious Metals & Minerals	801203	retailing
801055	Industrial Metal	801204	Specialty Retail
801072	General Industrial Machinery	801205	Commercial Property Service
801073	Instrument & Apparatus	801211	Catering
801074	Special Equipment	801212	Attractions
801075	Metal Products	801213	Hotel
801076	Transporting Facilities	801214	Leisure Conglomerates
801081	Semi-conductor	801222	Software
801082	Other Electronic Products	801223	IT Services
801083	Electronical Part & Component	801231	Conglomerates
801084	Optical & Opto-electronic Products	801711	Cement
801085	Electronical Manufacturing	801712	Glass Products
801092	Automobile Services	801713	Other Construction Materials
801093	Auto Parts & Equipment	801721	Homebuilding
801094	Automobile Manufacturers	801722	Decoration
801101	Computers & Peripherals	801723	Infrastructures
801102	Communications Equipment	801724	Specialty Engineering
801111	Household Appliances	801725	Landscape engineering
801112	Audiovisuals	801731	electrical machinery
801123	Beverage	801732	Electric Automation Equipment
801124	Food Products	801733	power supply equipment
801131	Textiles	801734	High-Low-voltage Switch Equipment
801132	Apparel	801741	Aerospace Equipment
801141	Packaging & Printing	801742	Aviation Equipment
801142	Household Products	801743	Defense Equipment
801143	Paper Products	801744	Shipbuilding
801151	Chemical pharmacy	801751	Advertising & Broadcasting
801152	Biotechnology	801752	Internet Media
801153	Health Care Equipment	801761	Culture Media
801154	Health Care Distributors	801881	Other Transporting Equipment

Appendix-B. Summary of minute-per-minute returns of the SWS securities industry indices

Index	Mean(‰)	SD (%)	Skew	Kurt	JB test	AR1	ADF
801011	-0.903	16.065	0.746	12.393	13395***	-0.312***	-15.291***
801012	-0.681	5.323	-0.205	6.578	1921***	-0.167***	-14.535***
801013	-0.81	16.37	0.212	8.831	5061***	-0.245***	-16.544***
801014	-1.978	11.613	1.438	39.187	195139***	-0.027***	-15.595***
801015	-0.343	7.478	-0.501	8.214	4175***	-0.292***	-14.733***
801016	-0.169	7.627	7.071	241.454	8449653***	0.011***	-15.491***
801017	-2.167	12.145	1.729	44.891	261638***	-0.048***	-14.903***
801018	-1.939	9.717	-0.05	12.299	12805***	-0.115***	-15.709***
801021	-0.169	5.56	-0.977	37.747	179355***	0.003***	-14.786***
801022	1.28	11.014	-0.096	5.133	679***	-0.344***	-16.618***
801023	1.131	11.162	0.001	3.123	2	-0.452***	-17.112***
801024	1.362	7.237	0.04	8.987	5308***	-0.142***	-13.563***
801032	0.436	5.511	0.157	9.999	7268***	-0.066***	-14.094***
801033	-0.763	5.942	-0.425	10.867	9271***	-0.136***	-14.543***
801034	-0.034	4.086	-2.999	111.755	1756809***	0.155***	-14.632***
801035	0.543	8.122	-0.022	3.004	0	-0.433***	-15.593***
801036	0.146	6.713	3.799	114.012	1833495***	-0.053***	-15.153***
801037	0.301	5.605	-0.742	15.213	22414***	-0.11***	-14.207***
801041	0.951	9.368	0.377	24.26	67013***	-0.201***	-14.351***
801051	-0.608	5.895	-1.513	29.834	107985***	0.054***	-14.748***

801053	1.742	11.145	-0.355	70.667	678131***	-0.153***	-15.589***
801054	2.997	7.955	2.589	40.927	216983***	0.062***	-15.215***
801055	-0.042	5.526	-0.366	7.556	3154***	-0.233***	-13.098***
801072	-0.799	4.243	-1.937	76.396	799947***	0.084***	-14.131***
801073	3.452	6.1	1.167	25.485	75674***	0.018***	-15.159***
801074	-1.047	4.677	-2.233	58.968	466814***	0.06***	-14.793***
801075	0.098	5.48	-0.329	8.875	5175***	-0.141***	-13.245***
801076	-0.068	7.743	0.124	6.562	1888***	-0.332***	-15.222***
801081	0.45	10.877	-0.902	26.515	82365***	0.105***	-13.42***
801082	0.194	7.866	0.627	11.823	11760***	0.077***	-14.136***
801083	-1.317	9.022	-1.62	33.36	138049***	0.068***	-13.503***
801084	-0.144	8.405	-1.465	30.54	113585***	0*	-14.966***
801085	0.205	9.623	-0.513	24.526	68771***	0.081***	-14.303***
801092	0.746	12.032	-0.273	6.601	1964***	-0.359***	-16.821***
801093	0.464	5.12	-1.222	75.057	769773***	0.053***	-15.378***
801094	-0.855	5.687	-0.783	28.128	93863***	-0.021***	-16.051***
801101	-1.415	7.657	-2.453	55.807	416502***	0.1***	-14.612***
801102	-1.525	6.582	-3.256	105.064	1548860***	0.165***	-14.506***
801111	-1.699	7.908	-4.988	116.867	1934734***	0.082***	-13.435***
801112	0.67	8.655	-0.004	6.449	1762***	-0.261***	-13.704***
801123	0.02	5.659	0.076	14.317	18970***	0.101***	-14.104***
801124	-0.563	6.134	-0.148	17.297	30282***	-0.025***	-14.013***
801131	-0.056	4.318	-0.34	19.892	42321***	-0.108***	-13.335***
801132	-1.593	5.244	-4.632	115.477	1886105***	-0.049***	-14.272***
801141	-0.478	5.487	-0.3	9.228	5797***	-0.002***	-14.648***
801142	-0.532	4.744	-1.367	45.758	271836***	0.025***	-14.31***
801143	-0.433	6.842	-0.82	10.068	7796***	-0.112***	-15.213***
801151	0.74	5.486	0.174	45.784	271083***	0.119***	-15.87***
801152	-1.356	6.436	-1.093	25.637	76590***	0.161***	-12.885***
801153	-1.334	6.454	-1.359	26.376	82010***	0.16***	-12.518***
801154	-1.427	4.945	0.03	12.11	12290***	-0.026***	-13.718***
801155	-1.345	4.754	-2.261	53.329	378124***	0.16***	-14.2***
801156	-2.577	8.67	-0.426	17.912	33035***	0.09***	-12.896***
801161	-0.411	4.091	-0.905	24.588	69499***	-0.161***	-14.244***
801162	-0.152	4.254	-0.526	19.486	40411***	0.012***	-12.533***
801163	-0.31	5.695	-0.632	23.393	61819***	-0.038***	-15.138***
801164	-0.563	5.913	-0.219	5.001	622***	-0.338***	-13.14***
801171	-0.084	6.469	-0.147	4.522	356***	-0.354***	-13.978***
801172	0.622	6.596	-0.309	20.147	43595***	-0.274***	-14.805***
801173	0.619	9.279	-0.044	5.41	861***	-0.343***	-14.24***
801174	0.729	7.313	0.034	11.978	11938***	-0.076***	-12.674***
801175	0.723	3.825	-0.373	6.507	1904***	-0.279***	-13.566***
801176	1.587	8.194	0.751	12.524	13767***	-0.169***	-13.217***
801177	0.174	8.336	0.144	5.303	797***	-0.403***	-15.965***
801178	-1.142	4.751	-1.183	26.155	80226***	-0.044***	-14.08***

801181	-0.869	4.372	-1.865	61.322	505764***	0.075***	-14.24***
801182	-0.189	5.001	-0.036	50.9	339765***	-0.117***	-13.432***
801191	-0.07	6.451	-0.567	23.318	61325***	-0.087***	-14.984***
801192	-0.726	4.571	0.141	15.213	22100***	-0.124***	-15.312***
801193	-0.799	6.114	1.626	58.392	455934***	0.08***	-14.999***
801194	-1.106	5.455	0.029	20.385	44756***	0.027***	-15.165***
801202	0.073	5.736	-0.133	14.933	21097***	-0.234***	-14.441***
801203	0.529	4.123	-0.237	21.943	53169***	-0.104***	-13.023***
801204	-0.132	6.666	0.083	10.175	7627***	-0.214***	-15.7***
801205	0.129	7.235	0.473	15.382	22836***	-0.29***	-15.406***
801211	-3.334	11.18	0.032	6.149	1469***	-0.199***	-15.77***
801212	-0.138	8.416	0.541	16.227	26081***	-0.216***	-15.32***
801213	3.7	10.659	1.261	22.761	58767***	-0.067***	-13.902***
801214	-1.14	9.226	-0.885	34.51	147491***	-0.023***	-14.829***
801222	-0.788	6.87	-2.365	79.895	878908***	0.165***	-14.683***
801223	0.796	11.852	0.029	6.514	1829***	-0.352***	-15.129***
801231	-0.16	5.522	-0.291	34	142354***	-0.1***	-14.273***
801711	1.899	8.488	3.049	77.688	831555***	0.12***	-15.411***
801712	1.441	8.734	0.216	7.709	3311***	-0.252***	-15.216***
801713	0.895	5.733	0.907	22.886	59051***	0.016***	-15.016***
801721	0.191	9.769	0.134	4.434	315***	-0.382***	-15.273***
801722	0.785	5.303	-1.06	22.936	59520***	-0.116***	-16.152***
801723	0.678	5.343	0.459	15.852	24586***	-0.093***	-12.759***
801724	0.836	6.232	-0.05	6.752	2086***	-0.3***	-13.615***
801725	-1.986	6.082	-0.631	21.37	50208***	-0.222***	-14.937***
801731	1.57	8.162	-0.619	18.209	34482***	-0.108***	-15.183***
801732	0.149	6.248	-0.255	12.16	12463***	-0.045***	-14.955***
801733	2.507	6.899	6.863	213.396	6583022***	0.032***	-14.506***
801734	-0.391	4.735	-1.798	57.386	439925***	-0.015***	-14.019***
801741	1.939	5.806	2.174	50.854	341915***	-0.065***	-14.438***
801742	1.342	4.438	-0.222	13.912	17663***	0.096***	-13.931***
801743	1.086	5.518	0.065	16.33	26314***	-0.145***	-15.402***
801744	-0.54	9.756	0.483	98.549	1352077***	-0.143***	-16.34***
801751	-0.737	8.929	-0.352	7.031	2480***	-0.176***	-14.61***
801752	1.823	7.355	-1.207	45.102	263352***	0.132***	-13.324***
801761	-1.072	4.977	-1.975	36.741	170898***	0.034***	-13.108***
801881	0.67	7.784	0.006	7.847	3479***	-0.189***	-15.836***