Characteristic Evolution of Inter-Industry Liquidity Spillover Effect in China's Stock Market -- An Analysis based on Complex Network

Siwen Li[1, *], Yiquan Zhao[1, a], Haoyuan Feng[2, b], Yaqiang Lu[1, c], Xueliang Dai[1, d]

[1]Business School, Soochow University, Suzhou, China

[2]School of Economics and Management, University of Chinese Academy of Sciences, Beijing, China

*Corresponding author: 13390618630@163.com, [a]2241820780@qq.com, [b]245675631@qq.com, [c]794476638@qq.com, [d]1025750661@qq.com

Abstract. In recent years, the liquidity risk of China's stock market occurs frequently and spreads among different industries. The study of liquidity spillover is of great significance to prevent systematic financial risk. Based on the industry transaction data of China's stock market from 2011 to 2021, this paper calculates the market liquidity of different industry indexes, constructs Granger causality network in stages, and discusses the heterogeneity of the spillover effect of liquidity at the industry level in different economic stages. It is found that there is a significant liquidity spillover effect among industries; Compared with the stage of high leverage and loose monetary policy, under the background of stable macro leverage ratio and stable monetary policy, the liquidity spillover effect among industries will be weakened; The impact of liquidity has gradually changed from the spillover impact of traditional industries to the spillover impact of emerging industries.

Keywords: Liquidity spillover effect; VAR model; Granger causality network; Systematic risk; Leverage.

1. Introduction

Liquidity is a measure of the market's ability to quickly conclude asset transactions at a reasonable price and is fundamental to the health of financial markets. Liquidity has a spillover effect [1], and the 2008 financial crisis was essentially a contagion of liquidity crises in global financial markets [2]. With the frequent outbreak of liquidity crises and the development of macro-prudential regulation in recent years, it is important to study the spillover of liquidity to prevent systemic financial risks and stabilize financial markets. Theoretically, the current literature on the transmission of stock market liquidity risk is mainly about the co-movement relationship of liquidity and less about liquidity spillovers, especially the study of inter-industry liquidity spillovers of the stock market.

Therefore, this paper measures the market liquidity of different industry indices based on industry trading data of the Chinese stock market from 2011-2021, and constructs Granger causality networks to try to clarify the evolution of the characteristics of industry-level liquidity spillovers under different economic stages and the heterogeneity between industries. This paper attempts to answer the following three questions: 1) whether there are significant spillovers between industries in the Chinese stock market; 2) whether the spillovers are heterogeneous across industries; 3) whether the characteristics of spillovers differ across economic stages.

2. Literature review and theoretical analysis

2.1 Liquidity spillover effect

The spillover effect refers to the fact that markets are not only affected by their own lagged variables, but also significantly affected by other markets [3]. Liquidity spillover refers to the interaction of multiple markets in liquidity. Chordia [1] points out that the liquidity of stocks has strong or weak characteristics in different industries from a time perspective. Kan Xiancheng [4] used six liquidity indicators to examine the variability and consistency of stock liquidity across industries and

found that there was some variability in cross-sectional spatial liquidity but some consistency in time. Jin Chunyu [5] found that there is liquidity spillover between industries through a BVAR model, and that the direction of spillover and influence of each industry differs significantly.

2.2 Analysis of the causes of inter-industry liquidity spillovers

The theory of market contagion derived from behavioural finance can explain the spillover effect of inter-industry liquidity in financial markets. Kyle and Xiong [6] constructed a wealth effect model to explain the mechanism underlying the significant increase in correlation between assets when asset prices fall, which is the contagion mechanism. Brunnermeier [7] proposed the liquidity spiral theory, arguing that the deterioration of financing liquidity and market liquidity during a crisis mutually reinforcing each other. Under conditions of high leverage, both the contagion of risk and the liquidity spiral effect will intensify [8], and loose monetary policy is an important reason for the increase in leverage [9]. As we will confirm below, liquidity spillovers will be more intense in a loose monetary policy environment.

The mechanism of liquidity spillovers can also be explained by "flight-to-liquidity", whereby investors attract a lot of capital into an industry when the market is performing well, and sell off assets into other industries when the market is not performing well. Investors can allocate assets and hedge risks across different markets to maximize their effectiveness. This cross-market and cross-industry portfolio will make capital markets in different industries more closely linked and enhance the flow of capital between sectors. In the short term, therefore, changes in liquidity in one industry may show a negative relationship with another industry.

In addition, Goetzmann [10], Ukhov [11] and Longstaff [12] conducted empirical studies on the factors affecting the liquidity spillover effect and concluded that macroeconomics, external environment and market information are significant factors, and the consistency of investor behaviour and investor emotions are also contributing to the liquidity spillover effect in the stock market.

The main contributions of this paper are as follows: Firstly, there is a shortage of research on liquidity spillovers at the industry level in equity markets, and this paper fills this gap. Secondly, the network model is constructed to not only capture the directionality of the liquidity relationship between industries, but also to characterise risk spillovers as a whole, as compared to the traditional liquidity correlation effects measured by the "goodness of fit" [1] and "β" [13]. Financial entities in some cases are linked by "co-occurrence" in the form of similarities or correlations, and co-occurrence networks can reveal obscure and unpredictable higher-order properties. The analysis of networks can improve the performance of risk modelling. Thirdly, previous research has ignored the heterogeneity of equity markets across industries. Identifying the main sources of liquidity risk at the industry level allows for more accurate management of liquidity risk. Moreover, it is highly likely that an industry will change from being spill-out of liquidity to spill-in at different stages, which also has important implications for financial regulation.

3. Research design and data

This paper divides 2011-2021 into two phases, using 31 May 2016 as the boundary, based on China's macroeconomic policy orientation: the first five years are the phase of loose monetary policy, high leverage and prevalence of shadow banking; the second five years are the phase of "deleveraging" and "preventing financial risks". Then, this paper measures the daily liquidity indicators of 19 industry indices of the A-share market under the two phases respectively, and constructs a VAR model for the series of liquidity indicators of 19 industries in two phases. In order to explore the spillover effects, this paper conducts Granger causality tests in two stages and constructs Granger causality networks based on F-values as weights and Granger causality as linked edges respectively. Finally, the characteristics and industry heterogeneity of industry liquidity spillovers under different stages are investigated by comparing the topological properties of the networks in the two stages.

3.1 Liquidity measures

In this paper, Amihud indicator is selected as a measure of the level of liquidity in the industry. Amihud [14] uses the ratio of the return of an individual stock to its trading volume to represent the illiquidity of a stock in the following form:

$$Amihud_{i,d} = \frac{(H_{i,d} - L_{i,d}) / O_{i,d}}{VO_{i,d}}$$

$H_{id}, L_{i,d}. O_{i,d}$ are the highest, lowest and closing prices of the industry i index on day d respectively, and VO_{id} is the trade value of the sector i index on day d, screening out trade days where the highest and lowest prices are equal or where the trade value is zero. $Amihud_{id}$ is the illiquidity indicator for industry i index on day d. It indicates the average price volatility per unit of transaction amount that the sector index has to endure during a single trading day. Smaller transaction amounts and greater price volatility will increase the value of this indicator, and thus larger values represent less liquidity for the index.

3.2 Granger causality networks and the nature of network topology

After the optimal lag order has been determined for the VAR model, Granger causality tests are carried out on this basis. The application of Granger causality to complex networks is more effective in revealing the true internal linkages between variables in complex networks. A Granger causality test is conducted on the panel data of industry liquidity indicators by adding a directional edge from the "Granger cause" to the "Granger result" between the two nodes, and a directional Granger causality network is obtained after all variables are tested.

This paper constructs a bidirectional Granger causality network for 18 industry liquidity indices for the whole sample and two stages respectively, using the F-value statistic as the weight of the edges to define the distance of the nodes in the network. A significance level of 10% was taken and statistical Granger causality tests were conducted for significant F-values, with insignificant ones recorded as 0. This paper focuses on several network topological properties as follows.

Table 1. Topological properties of Granger networks

Topological properties	Mathematical expressions	Nature Meaning
Network density	$\frac{\sum_{i=1}^{n}\sum_{j=1}^{n} G(i,j)}{n(n-1)}$	A higher network density means that the whole system is more connected.
Average path length	$\frac{\sum_{i\neq j} d_{i,j}}{n(n-1)}$, $d(i,j)$ means the distance between i and j	A smaller average path length implies a faster rate of impact between industry liquidity.
Network Diameter	Distance between the two nodes with the longest shortest path	The smaller the diameter of the network, the more interconnected and connected the whole system is.
Average aggregation coefficient	$\frac{\sum_{i=1}^{n} \frac{2L_i}{k_i(k_i-1)}}{n}$	A higher average coefficient of aggregation implies a stronger degree of connectivity between industries.

In this paper, the F-statistic is used to define the degree of mutual influence of liquidity between industries. The process of calculating the F-statistic reflects the degree of significance of the causal relationship of liquidity between industries. In this paper, the sum of the F-values of each industry as a "Granger cause" to the other "Granger results" is defined as the liquidity spill-out of an industry. The sum of the F-values of the other "Granger causes" to an industry when it treated as a "Granger result" is defined as the liquidity spill-in of an industry. When the liquidity spill-out of an industry is greater than the spill-in, namely the net spillover is greater than zero, the industry has more influence on other industries in the network; when the industry's liquidity spill-out is less than the spill-in, namely the net spillover is less than zero, the industry is more influenced by other industries in the network.

3.3 Data and descriptive statistics

This paper selects daily data of the SEC Tier 1 Industry Index from 2011.08.01 to 2022.04.01, including 2594 trading days. Covering 19 industries classified by the SEC, all data are obtained from the Choice Financial Database. Due to the insufficient number of listed companies in the residential services industry, this industry was excluded and 18 industries were finally identified.

Liquidity time series data for all industries were obtained using the above measures and the descriptive statistics of industry liquidity indicators are shown in Table 2.

Table 2. Descriptive statistics for liquidity indicators

Name of industry	Variable name	Sample size	Mean (10^-12)	SD (10^-12)	Maximum (10^-13)	Minimum (10^-12)
Agriculture, forestry and fishing	I1	2594	5.481	5.039	7.0207	0.667
Mining	I2	2594	70.36	253.292	363.3129	0.179
Manufacturing	I3	2594	0.107	0.115	0.0896	0.005
Electricity, heat, gas and water production and supply	I4	2594	2.403	2.482	1.9233	0.188
Construction	I5	2594	2.484	2.35	2.2588	0.212
Wholesale and retail trade	I6	2594	1.508	1.4	1.184	0.187
Transport	I7	2594	2.619	2.761	2.2573	0.276
Accommodation and catering	I8	2594	48.468	41.339	107.1464	5.31
Information Technology	I9	2594	1.262	1.715	1.6984	0.071
Finance	I10	2594	0.612	0.528	0.3565	0.08
Real Estate	I11	2594	1.639	1.307	1.1207	0.174
Rental and business services	I12	2594	8.304	10.488	7.3242	0.616
Scientific Research and Technology Services	I13	2594	26.639	47.93	103.0724	0.428
Water, Environment and Utilities Services	I14	2594	8.351	8.407	7.1877	0.7
Education	I15	2594	1058.08	2404.743	2315.7442	5.298
Health and Social Work	I16	2594	83.555	119.319	152.8406	1.908
Culture, Sports and Recreation	I17	2594	6.721	8.232	7.2879	0.644
General	I18	2594	11.819	9.137	7.8822	1.118

4. Inter-industry liquidity spillover effects in the stock market

After the ADF test, the liquidity series of all industries are smooth in both the full sample and the two stages. The optimal order of the VAR model was then determined in the three experiments, with the optimal order of the VAR model being 8 in the full stage 2011.08.01-2022.04.01; 4 in the first stage 2011.08.01-2016.05.31; and 5 in the second stage 2016.06.01-2022.04.01.

Based on the VAR model, this paper first constructs a Granger causality network for the overall sample, followed by separate networks for the two stages, and the results are as follows.

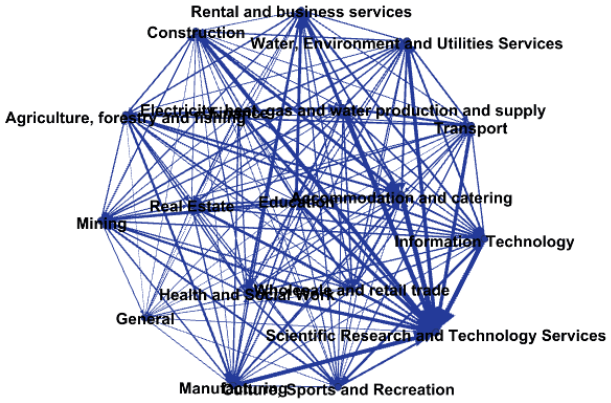

Figure 1. Overall Granger causality network

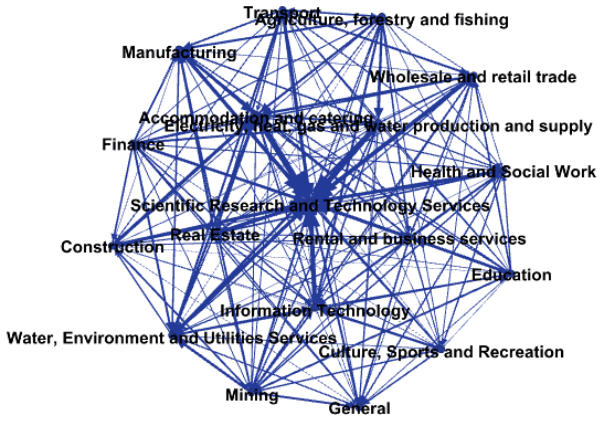

Figure 2. 2011.08.01-2016.05.31 Network

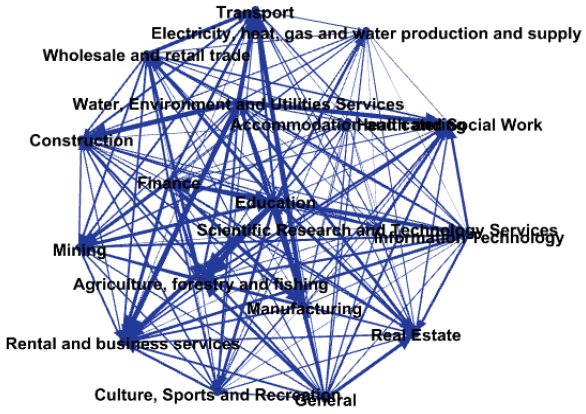

Figure 3. 2016.06.01-2022.04.01 Network

Based on the Granger causality network, the following network topology properties were obtained.

Table 3. Topology properties of network

Topology properties	Integral	Stage 1	Stage 2
Network density	0.974	0.833	0.703
Average path length	1.026	1.167	1.297
Network Diameter	2	2	2
Average aggregation coefficient	0.974	0.834	0.706

Table 3 shows that there are significant liquidity spillovers between industries in the Chinese equity market; the liquidity spillovers between industries are mitigated and the characteristics of liquidity spillovers between industries change significantly in the two time periods before and after the time period divided on the basis of leverage and monetary policy; there is significant heterogeneity in the liquidity spillovers between industries. The specific analysis is as follows.

4.1 Liquidity spillover effects in the stock market

In the Granger causality network constructed using the overall sample data, the network density is 0.974, implying that there is a significant phenomenon of liquidity spillover effect between industries in Chinese stock market; the network diameter and the average aggregation coefficient can reflect the degree of network connectivity, and these indicators are high overall; the average path length is 1.026, indicating that the transmission of liquidity spillover effects between industries is relatively fast.

By phase, the density of the network in the period 2011.08.01 - 2016.05.31 is lower than that in the period 2016.06.01 - 2022. 04.01, which indicates that under the background of stable macro leverage and prudent monetary policy, the liquidity spillover effect between industries is significantly mitigated and the systemic risk formed by the transmission of liquidity risk between industries is reduced, which is consistent with this paper's theoretical analysis. The average aggregation coefficients are higher in the first stage than in the second stage, with a higher degree of connectivity between industries in the first stage. The average path length in the first stage is smaller than that in the second stage, so liquidity spillovers between industries are faster in the first stage.

4.2 Heterogeneity analysis of liquidity spillovers among industries

The liquidity spillover effects of industries at each stage are shown in Figures 4 and 5. From the graphs comparing spill-in and spill-out, it can be obtained that there is significant heterogeneity in the liquidity spillover effects across industries, and the characteristics of liquidity spillover between industries in the second stage have produced significant changes in comparison with the first stage.

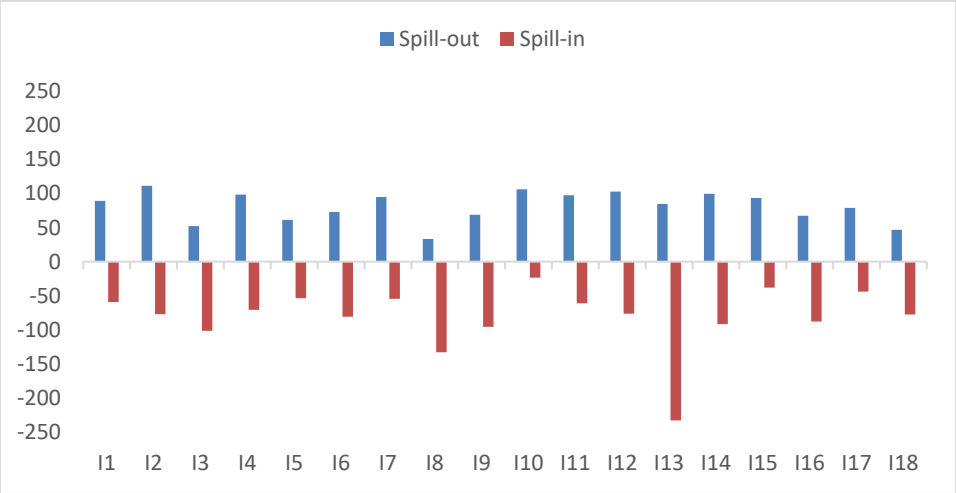

Figure 4. 2011.08.01-2016.05.31 Liquidity spill-in and spill-out effects

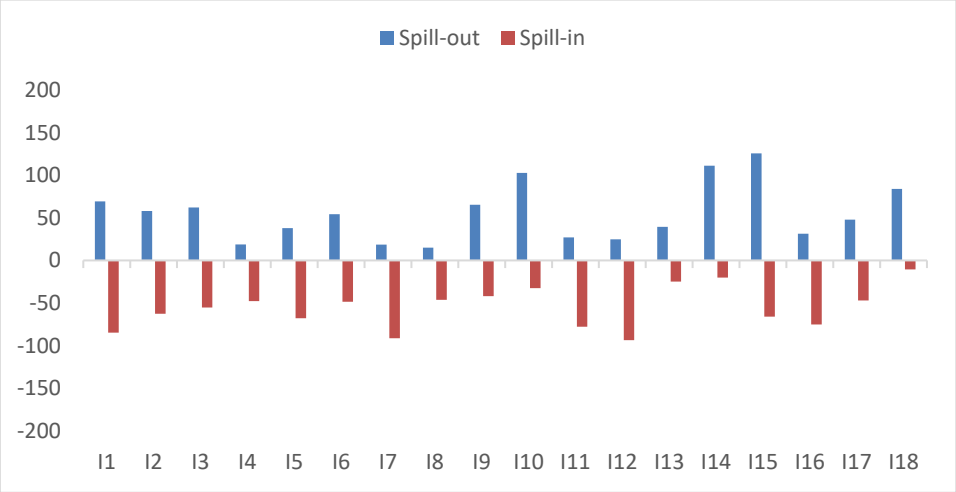

Figure 5. 2016.06.01-2022.04.01 Liquidity spill-in and spill-out effects

There is greater heterogeneity in the spillover effects among industries: the industries with higher net spillover and higher spillover capacity in the first stage are I10 (Finance), I15 (Education) and I7 (Transport); the industries with higher net spillover and higher spillover capacity in the second stage are I14 (Water, environment and utilities services), I10 (Finance) and I15 (Education). Finance and education are consistently net spillovers, and the spillover effect is significantly higher in the second stage. This suggests that the health of financial markets is important in influencing the overall industry's liquidity.

I1 (Agriculture, forestry and fishing), I2 (Mining), I4 (Electricity, heat, gas and water production and supply), I5 (Construction), I7 (Transport), I11 (Real estate) and I12 (Rental and business services) have shifted from net spill-out in the first stage to net spill-in. I3 (Manufacturing), I6 (Wholesale and retail trade), I9 (Information technology), I13 (Scientific research and technical services) and I18 (General) changed from net spill-in to net spill-out in the first stage. The industries that changed from net spill-in to net spill-out were mainly frontier industries.

5. Conclusion

This paper investigates the liquidity spillover effect among industries in the Chinese stock market using Granger causality networks and demonstrates that there is a significant liquidity spillover effect between industries. This spillover effect shows different characteristics in different economic contexts: compared to the liquidity spillover effect in a phase of high leverage and loose monetary

policy, the liquidity spillover effect is weaker in a stable macro leverage ratio and moderate monetary policy. This paper focuses on the heterogeneity of industry liquidity spillovers to identify the key industry groups that have a greater impact on other industries. The findings show that there is heterogeneity in liquidity spillovers and spillovers for different industries, and that the characteristics of liquidity spillovers change with the times, gradually shifting from the spillover effects of traditional industries to those of emerging industries.

Acknowledgements

Undergraduate Training Program for Innovation and Entrepreneurship, Soochow University.

References

[1] Chordia T, Roll R, Subrahmanyam A. Commonality in Liquidity [J]. Journal of Financial Economics, 2000, 56(1): 3-28.

[2] Nagel S. Evaporating Liquidity [J]. Cepr Discussion Papers, 2012, 25(7): 2005-2039.

[3] Amman M. and Zimmerman. H, Tracking Error and Tactical AssetAllocation [J], Financial Analysts Journal, 2001, 57: 32-43

[4] X. C. Kan, J. B. Huang, Research on Difference and Commonality of Liquidity Between Different Industries Stocks [J]. Journal of Nanjing University of Finance and Economics, 2007(03): 46-49.

[5] C. Y. Jin, H. B. Zhang. A study of the spillover effects of industry sector liquidity in the Chinese stock market [J]. Economic Review Journal, 2016(12): 103-106.

[6] Kyle, Albert S., and Wei Xiong. 2001. "Contagion as a Wealth Effect," Journal of Finance, 56(4): 1401~1440.

[7] Brunnermeier, Markus K., and Lasse Heje Pedersen. 2009. "Market Liquidity and Funding Liquidity" Review of Financial Studies, 22(6): 2201~2238.

[8] Adrian, T., and H. S. Shin. Liquidity and Leverage [J]. Journal of Financial Intermediation, 2010, 19(3), 418-437.

[9] Gulen, H. and Ion, M., 2016, "Policy Uncertainty and Corporate Investment", Review of Financial Studies, 29(3), pp. 523-564.

[10] Goetzmann W N, Massa M. Daily momentum and contrarian behavior of index fund investors [J]. Journal of Financial and Quantitative Analysis, 2002, 37(3): 375-389.

[11] Ukhov A D, Goyenko R Y, Stock and bond market liquidity: A long-run empirical Analysis [J], Journal of Financial and Quantitative Analysis, 2009, 44(1): 189-212.

[12] Longstaff, F. A., The Flight - to -Liquidity Premium in U.S. Treasury Bond Prices, journal of Business, 2004 (77), 511~526.

[13] G. Andrew Karolyi, Kuan-Hui Lee, Mathijs A. van Dijk. Understanding commonality in liquidity around the world [J]. Journal of Financial Economics, 2012, 105 (1).

[14] Amihud, Y. "IIliquidity and Stock Returns; Cross-section and Time-series Effects." Journal off inancial markets, 2002, 5(1), pp.31-56.