Chinese New Media Stocks Liquidity Risk and Spillover Effect

Yinuo Zhao, Yuxin Kang and Kun Guo

December 7, 2022

9th International Conference on Information Technology and Quantitative Management

Chinese New Media Stocks Liquidity Risk And Spillover Effect

Yinuo Zhao[a], Yuxin Kang[b], Kun Guo[c, d] *

[a] New York University, 721 Broadway, New York 10003, U.S.

[b] Sino-Danish College, University of Chinese Academy of Sciences, Beijing 100190, China

[c] School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100190, China

[d] Research Center on Fictitious Economy & Data Science, Chinese Academy of Science, Beijing 100190, China

Abstract

Since the beginning of the 21st century, China's new media industry has attracted more and more investors' attention with its rapid development. However, its stock market has consistently shown unstable performances in recent years. In this study, we explore the interconnections between new-media stocks by conducting liquidity risk and liquidity spillover analysis between individual stocks and markets. We find that the instability of China's new media stocks stems from the volatility of idiosyncratic risks and high systemic correlation across markets, which collectively contribute to higher liquidity risk spillover effects.

Keywords: New Media Stock, Liquidity Risk, Liquidity Spillover Effects, Risk Management

1. Introduction

On April 20, 1994, China realized the first full-featured TCP/IP link with the global Internet and truly became a new member of the new media family. Scholars and media people began to observe and explore the development of new media, as well as investors whose attention started to shift from traditional media to this revolutionary field. Because of China's extensive population base, quick localization and diversification of labor resources bolstered the rapid growth of the new media industry in the coming decades. Investors' interests continued to escalate with the increasing number of new media stocks managed to list on exchange markets inside and outside China.

---

* Corresponding author.
E-mail address: guokun@ucas.ac.cn

The rapid expansion and development are also attributed to several inherent advantages of new media, compared to the traditional ones. First, a new media firm's business mode is usually diversified, crossing or even converging multiple platforms to adhere to the highly segmented consumers. Second, new media reduces a firm's dependence on advertisers, which strengthens its own economic and operational independence. At last, this new business model is significantly conducive to the interconnection of various media, and the optimal allocation, integration, and utilization of resources, therefore improving physical and economic efficiency.

On the other hand, new media firms challenge their investors with higher complexity and difficulty to obtain an intuitive view of the big-picture. The aforementioned advantages of new media firms cause their stocks to endure corresponding characteristics, such as greater market volatility, higher possibility of concept sensationalization, unvalued asset bubble, underestimated risk premium, unexpected systemic risk contagion...etc. In recent years, stocks from many Chinese new media firms have experienced notable, large fluctuations after listing. Therefore, based on the general characteristics of new media stocks, this study explores the attributes of their liquidity changes, and further examines the spillover effect of liquidity risk between individual stocks and between different markets; thereby providing evidential support for market risks and liquidity risks management related to Chinese new media stocks.

2. Literature Review

Among all measures of risks, the studies of liquidity have been crucial for policymakers to supervise and restore balance in financial systems when they are destabilized by systemic risks. Yet, the elusive nature of liquidity makes it difficult to be evaluated using one single measure. "The word liquidity has so many facets that are often counter-productive to use it without further and closer definition", remarked Charles Goodhart[1].

In general, market liquidity should reflect its ability to trade. According to Anibal Fernandez, market liquidity has three key elements: volume, time, and transaction [2]. A liquid market should allow assets to be sold anytime within market hours, rapidly, with minimum loss of value, and at competitive prices. When the probability of not being liquid equals unity, liquidity risk reaches maximum and illiquidity materializes [3]. This direct, inverse relationship signifies the importance of thorough examination and correct pricing of liquidity risks. Pastor and Stambaugh noted that market-wide liquidity acts as a state variable for common-stock pricing. They found that the expected stock returns are closely related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity[4]. Angelidis and Andrikopoulos also stressed in their study that there are bidirectional causal relations between shocks in idiosyncratic/systemic risks, liquidity, and expected returns[5]. Systemic and idiosyncratic risk affects liquidity, which affects expected returns and returns are determined by idiosyncratic risk[6][7]. Further, Angelidis and Andrikopoulos also discovered volatility spills over from large to small-cap stocks and vice versa and can be predicted by illiquidity shocks. In this study, we are going to further explore the use of illiquidity as a measure of risk spillover within and across new media markets.

In 1986, Amihud and Mendelson proposed a hypothesis on the positive cross-sectional return-liquidity relationship, in which the stock expected return is an increasing function of stock illiquidity[8]. This hypothesis was further tested and proved by Amihud in 2000 using a new measurement of stock illiquidity, called ILLIQ, in which he used the daily ratio of absolute stock return to its dollar volume, averaged over a certain period:

For each year y, the illiquidity measure of stock is calculated as the average

$$\text{ILLIQ}_{iy} = \frac{1}{D_{iy}} \sum_{t=1}^{D_{iy}} \frac{|R_{iyt}|}{\text{VOLD}_{iyt}}$$

(1)

,where $\frac{|R_{iyt}|}{\text{VOLD}_{iyt}}$ is the average ratio of the daily absolute return to the trading volume on that day. Riyt is the return on stock i on day t of year y and VOLDiyt is the respective daily volume in dollars, and Diy is the number of days for which data are available for stock i in year y [9].

This measure defines stock illiquidity as the average ratio of the daily absolute return to the trading volume on daily bases, giving the daily price impact of the order flow. Compared to other microstructure measures of illiquidity, such as bid-ask spread [8], transaction-by-transaction market impact [10][11], and the probability of information-based trading [12] which all require data on transactions and quotes unavailable in most markets around the world, ILLIQ can be obtained simply from data on daily stock returns and volume that is readily available to the public. Another advantage of this measure is that it enables the construction of long time series of illiquidity that is necessary to test the effects over time of

illiquidity. In this study, we are going to employ an approach in the spirit of the ILLIQ measure, using daily absolute stock returns and trading volume to generate a measure that can be used to evaluate new media stock liquidity across the time of a 7-year span. The daily analog of ILLIQ measure is defined as:

$$I_{i,t} = \frac{|r_{i,t}|}{Vol_{i,t}}$$

(2)

where Vol$_{i,t}$ and |r$_{i,t}$| are the trading volume and the absolute return on stock i on day t.

Moreover, studies have shown strong positive covariance between individual stock liquidity and overall market liquidity[3]. The dynamic propagation of liquidity risks across markets implies the significance of liquidity in terms of achieving financial stability, as unmanaged systemic liquidity risks might induce financial crises, disrupt the allocation of resources and unsettle the entire economy. Within China's exchange market, network connectedness between firms amplifies financial shocks through contagion effects [13]. Statistics have shown that China's systemic risk contagion has a cluster effect. Systemic risk contagion level varies among sectors, while correlation and size of financial institutions are crucial in affecting their systemic importance. In this study, we will focus on the correlations between new-media firms to measure systemic risk spillover effects within and across both domestic and foreign markets.

To evaluate the degree of interconnectedness and the direction of correlations between firms, we will employ the econometric measure of Granger causality[14]. X is said to "Granger-cause" Y if past values of X contain information that helps predict Y above and beyond the information contained in past values of Y alone. The mathematical formulation of this test is based on linear regressions of Y on X and X on Y. When market frictions, such as value-at-risk constraints, transaction costs, borrowing constraints, and institutional restrictions on short sales, exist in a market, Granger causality can be found among price changes of assets. Granger causality in asset returns is a proxy for the liquidity risk spillover among market participants. The more causalities detected, the tighter the connections among the firms, heightening the severity of systemic liquidity risk contagion across the market [14].

3. Data and Methodology

All samples used in this study are retrieved from investing.com, one of the three most globally acknowledged financial websites. Founded by Door Efrat in 2007, Investing provides its customers with authoritative information on stocks, futures, options, analysis, and commodities.

The primary sample pool consists of 105 Chinese companies traded on the Shanghai stock exchange, Shenzhen stock exchange, Hong Kong Stock Exchange, NYSE, and Nasdaq (the only five markets where the trading record of listed Chinese new media companies are publicly available). Further, the selection of sample was based on on each company's annual reports. Businesses in new media combined (including R&D, production, appliance, investing, promotion, or dissemination of new media) must contributed to their operational income as the largest source.

Once the sample pool was confirmed, daily data of all 105 companies were retrieved from Investing and separated into three sections: the closing price, earning yields and trading volume, starting from January 1st, 2017 to July 8th, 2022 (approximately five-year-span). During the data retrieving process, we found that a considerable proportion of samples' trading records were corrupted or missing data, not only on Investing but also on various other public databases. The deficiency of correct track records might cause problems for future investigators who would also like to look at this sector of the Chinese market.

To ensure the liability of data for further analysis, samples with a sizeable amount of incomplete trading records were discarded, leaving 54 companies available for further data filtering. Of all 54, 15 samples with over 10% of corrupted/missing data proportioned to their sample size were also filtered out. The last 39 samples' data were cleaned with the linear interpolation method independently, despite the situation where there was more than 1 month of data vacancy on the timeline. In such cases, data on earning yields and trading volume were set to zero to conserve the primitivity of data and prevent additional sacrifice on liability.

In this study, we are going to use the daily analog of ILLIQ, a measure of illiquidity proposed by Amihud (2000):

$$I_{i,t} = \frac{|r_{i,t}|}{Vol_{i,t}}$$

(3)

where $\text{Vol}_{i,t}$ and $|r_{i,t}|$ are the trading volume and the absolute return on stock i on day t. *ILLIQ* is based on the definition of stock illiquidity as the average ratio of the daily absolute return to the trading volume on daily bases. The resulting ratio, therefore, can be interpreted as the daily price impact of the order flow. This measure has two major advantages: 1)it only requires data that are readily available to everyone 2) it enables the construction of long time series of illiquidity that is necessary to test the effects over time of illiquidity. To measure the liquidity of samples, we are going to use the reciprocal of the daily analog of the ILLIQ measure to represent the liquidity of new-media stocks

$$L_{i,t} = \frac{\text{Vol}_{i,t}}{|r_{i,t}|}$$

(4)

.Although missing data on earning yields and trading volume have been cleaned and replaced with linear interpolation values, we are processing a large quantity of data containing daily earnings and trading volumes of 39 stocks through 5 years. Within, situations, when daily earning yields are zero, do exist in a considerable amount. In such cases, the denominator (daily absolute return of stocks) values would be zero, rendering the calculation unsolvable. This would leave us with a large quantity of missing data which would damage the correctness of future analysis with the Granger Causality Test.

Concerning this issue, we modified the measure by taking the exponential function of the absolute daily return, and using the result of this function as the new denominator:

$$LE_{i,t} = \frac{\text{Vol}_{i,t}}{e^{|r_{i,t}|}}$$

(5)

.Because we made this modification uniformly on the formula instead of on individual samples, this should not affect the objectivity of the results.

4. Empirical Analysis

4.1 General Observation Results

Descriptive statistics on the liquidity of individual stocks are shown below in Fig.1. We find a great variability of liquidity existing in the A-shares market. First, several stocks have significantly higher liquidity than others. The performance is uneven across the market. Second, these liquid stocks have very high SDs, and large gaps between mean and median, which indicates great variances in individual stock liquidity over the 5 years. These two findings signify the instability of idiosyncratic risks and market risks in the A-share market. The H-shares companies share similar symptoms, but with lower liquidity and the highest deviation of market-averaged liquidity among all three markets (see Fig.1). This phenomenon is complementary to our findings in the previous section, in which we mentioned the possibility of high volatility in the H-shares market. The U.S. market shares, compared to two other markets, have considerably lower liquidity. Nevertheless, it does have more stability in idiosyncratic risks, Especially from LE31 to LE 34, standard deviation comes below mean and median, implying a rather concentrated liquidity base. The differences between Chinese domestic markets and the U.S. market might be attributed to their low correlations mentioned before.
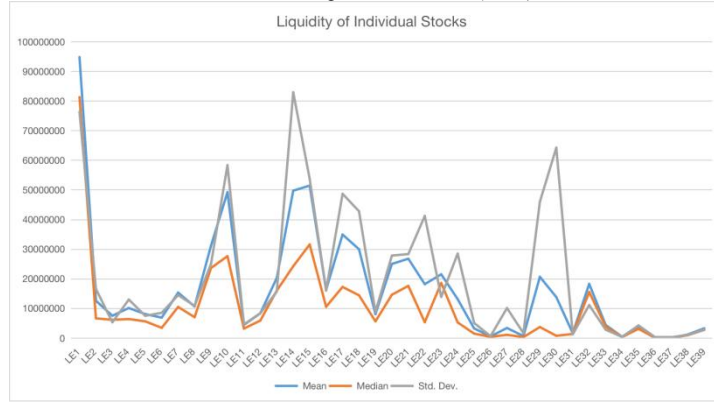
Fig. 1. This graph shows the mean, median, and SD of each stock's liquidity. LE1 to LE22 are A-shares, LE23 to LE30 are H-shares, and LE31 to LE39 are shares listed on U.S. exchange markets.

4.2 Correlations

Correlations between individual stocks' liquidity and between markets are visualized in Fig.2. Two interesting findings are discovered:

1) We noticed a higher correlation between each domestic market and the U.S. market in terms of liquidity. Although in an earlier analysis of earning-yields correlations, the U.S. market seemed to be quite isolated from the domestic markets, the liquidity of U.S. market shares seem to have higher connections with those of domestic markets (A-shares and H-shares). This suggests that the liquidity risk of new-media markets has the potential for market-wise and country-wise propagation.

2) With both graphs, we also discovered a possible negative correlation between the A-shares market and the H-shares market. Although the correlation appears weak on numbers, we would like to remind the readers that this result is generated with daily sample data over 5 years, therefore its existence should not be oversighted.
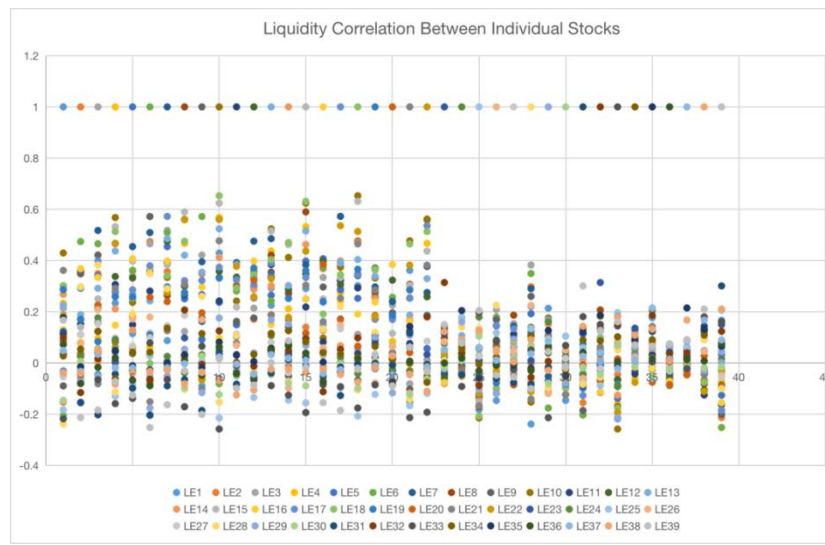

Fig. 2. (1) This graph shows the correlation of individual stocks' liquidity. LE1 to LE22 are A-shares, LE23 to LE30 are H-shares, and LE31 to LE39 are shares listed on U.S. exchange markets. The value of the x-axis corresponds with the values presented in the name of each stocks.
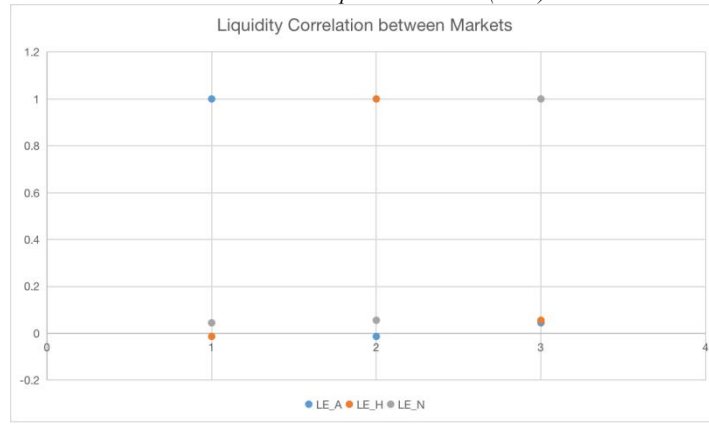
Fig. 2. (2) This graph shows the correlation of earning yields of each market. In the x-axis, 1, 2, and 3 each correspond with LE_A, LE_H, and LE_N. The data used in this graph is the result of averaged liquidity within each market, i.e. the sum of each individual stock's liquidity divided by the total number of samples within that market.

4.3 Liquidity Spillover Analysis

From our analysis of liquidity risks, we discovered clues of liquidity correlation among the three targeted markets of choice. In pursuance of consolidation of our findings, we will use the Granger causality tests to determine the degree and direction of their correlations.

Granger causality exists among all markets at different intensity levels. The density of red edges is significantly higher than blue and green edges, meaning A-shares market liquidity has a tighter interconnection. Hence, a higher possibility of liquidity risk spillover. This finding overlaps with our speculation that the A-shares market has higher interdependencies than the two other markets, based on its earning yields analysis. In Fig.3.(1), the Fort Atlas algorithm provides us with direct visualization of the spread of correlations by placing nodes with fewer connections farther, and vice versa. Opposing the highly connected A-shares nodes, the nodes of U.S. market liquidity are all placed on the edge of the diagram. The low correlation of U.S. market liquidity complements our findings of a similar situation in terms of stock return, as validated by Amihud's theory of positive cross-sectional return-liquidity relationship. However, in Fig.3.(2) which we use the Fruchterman Reingold algorithm, we discover that although the depth of correlations might be low, the spread of the U.S. market's influence is closely intertwined with the domestic markets (A-shares and H-shares). This would explain the higher correlation of liquidity mentioned previously. As a result, we find that although the depth of the U.S. market's involvement with the other two markets is low, the breadth of possible influence is higher than what one might expect.
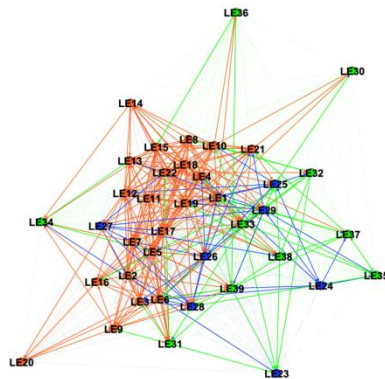

Fig. 3. (1) This network diagram uses the Fort Atlas force-directed layout algorithm to visualize the Granger causality relations between 39 stocks. Edges are colored in red, blue, and green, each corresponding to the A-shares market, H-shares market, and U.S. market. If one stock's liquidity "Granger causes" another stock's liquidity, the edge would be bolded.
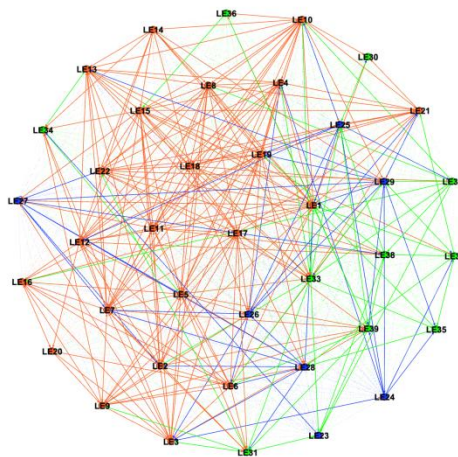
Fig. 3. (2) This network diagram uses the Fruchterman Reingold spatial layout algorithm to visualize the Granger causality relations between 39 stocks. Edges are colored in red, blue, and green, each corresponding to the A-shares market, H-shares market, and U.S. market. If one stock's liquidity "Granger causes" another stock's liquidity, the edge would be bolded.

The direction of correlation is also observed using these diagrams. Detailed findings are listed below:

    1) H-shares stock liquidity "Granger-causes" more than it is "Granger-caused" across markets.

    2) H-shares stock liquidity is more "Granger-caused" by the liquidity of A-shares stock than that of the U.S. market.

    3) A-shares stock liquidity mostly "Granger-causes" and be "Granger-caused" by stock liquidity within the market.

    4) U.S. market stock liquidity "Granger-causes" more than it is "Granger-caused" across markets.

These findings lead to several implications that might be useful for future systemic risk management related to the new-media market. First, the liquidity risk spillover effect exists inside and between the A-shares and H-shares market due to a profound density of correlations. Second, the A-shares market is highly interconnected and dependent within, which would heighten the severity of systemic risk during a financial crisis. Third, the H-share market risk is more likely to be influenced by the A-shares market (than the U.S. market). Liquidity spillover might occur between the two domestic markets and is most likely to be caused by the latter. At last, U.S. market liquidity risk can spill over to the domestic markets (A-shares and H-shares) even with a lower depth of correlation.

5. Conclusion

The diverse, unstable nature of the new-media market environment has posed challenges to risk assessment and management in recent years. In this study, we have shown how the evaluation of liquidity can act as a correlation variable to examine new-media stock's liquidity risk and its spillover effects. Derived from Amihud's *ILLIQ* measure, our measure of liquidity has allowed us to gain deeper insights into the correlations between new-media stocks and different markets with less restriction on the accessibility of data.

Combining our findings in both descriptive analysis and empirical analysis of three markets, we can conclude a few characteristics of the three markets. The A-shares market (including the Shanghai stock exchange and Shenzhen stock exchange) shows very strong interdependence between firms which might cause a greater possibility of systemic risk contagion. The H-shares market (Hong Kong stock exchange) shows the highest systemic volatility and most turbulent market environment. The U.S. market (including Nasdaq and NYSE) shows great stability in idiosyncratic risks but very high systemic volatility as we can observe from the uneven performance among different firms.

In terms of correlation between markets, we have found that the A-shares and H-shares markets are more closely correlated, while the A-shares market will act as the source of influence when coming to liquidity risk contagion within the domestic markets. There are also signs of high liquidity spillover within the A-shares market itself. We also found that the liquidity risk of the U.S. market can spill over to the domestic markets within the new-media industry. The intensity of its influence might be low, but the scale of propagation is profound.

At last, we want to encourage future investigators and scholars to keep constant examinations on the health of the Chinese new-media stock market. From our own experience, the tracking and supervision of new-media-stock-market

records showed very poor performances compared to other industries. We want to stress the importance of monitoring the financial stability of the new-media market because, unlike other fields, new media's foundation is based on drawing resources from various ranges of other industries. The lack of efforts in mitigating liquidity risk in the new-media market can result in irreversible damages to many other areas of the economy, causing misallocations of resources, employment difficulties, or even inducing a financial crisis. We would also suggest future research to investigate possible solutions, either regulatory or financial, that can facilitate risk control and rebuild stability in the Chinese new-media stock market.

Acknowledgement

References

[1] Goodhart, C. (2008), "Liquidity risk management." Financial Stability Review, Banque de France (February).

[2] Fernandez, F. A. (1999), "Liquidity Risk: New Approaches to Measurement and Monitoring." Securities Industry Association Working Paper.

[3] Nikolaou, Kleopatra. "Liquidity (Risk) Concepts: Definitions and Interactions." SSRN Electronic Journal, 2009.

[4] Pastor L. and R. F. Stambaugh (2003), "Liquidity Risk and Expected Stock Returns." Journal of Political Economy, University of Chicago Press, vol. 111(3), pages 642-685.

[5] Andrikopoulos, Andreas, and Timotheos Angelidis. "Idiosyncratic Risk, Returns and Liquidity in the London Stock Exchange: A Spillover Approach." SSRN Electronic Journal, 2008.

[6] Angelidis, T., & Tessaromatis, N. (2008). Idiosyncratic volatility and equity returns: UK evidence. International Review of Financial Analysis, 17, 539−556.

[7] Galariotis, E. C., & Giouvris, E. (2007). Systematic liquidity and excess returns: Evidence from the London Stock Exchange. 10th FMPM Conference, Zurich, March 2007.

[8] Amihud, Yakov, and Haim Mendelson. "Asset Pricing and the Bid-Ask Spread." Journal of Financial Economics, vol. 17, no. 2, 1986, pp. 223–249.

[9] Amihud, Yakov. "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." Journal of Financial Markets, vol. 5, no. 1, 2002, pp. 31–56.

[10] Brennan, Michael J. and Avanidhar Subrahmanyam, 1996, "Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns." Journal of Financial Economics 41, 441-464.

[11] Chalmers, John M.R. and Gregory B. Kadlec, 1998, "An Empirical Examination of the Amortized Spread." Journal of Financial Economics 48, 159-188.

[12] Easley, David, Soeren Hvidkjaer and Maureen O'Hara, 1999, "Is Information Risk a Determinant of Asset Returns?" Working Paper, Cornell University.

[13] Fan, Xiaoyun, et al. "Network Connectedness and China's Systemic Financial Risk Contagion——an Analysis Based on Big Data." Pacific-Basin Finance Journal, vol. 68, 2021, p. 101322.

[14] Billio, Monica, et al. "Econometric Measures of Systemic Risk in the Finance and Insurance Sectors." 2010.