

Winter 12-4-2017

Constructing Media-based Enterprise Networks for Stock Market Risk Analysis

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Recommended Citation

Xing, Rong; Dong, Shengxin; Wang, Qinyu; Li, Qing; Luo, Xubin; and Duan, Jiang, "Constructing Media-based Enterprise Networks for Stock Market Risk Analysis" (2017). *ICEB 2017 Proceedings*. 8.

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Constructing Media-based Enterprise Networks for Stock Market Risk Analysis

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ABSTRACT

Stock comovement analysis is essential to understand the mechanism of stock markets. Previous studies focus on the comovement from the perspectives of fundamentals or preferences of investors. In this article, we propose a framework to explore the comovements of stocks in terms of their relationships in Web media. This is achieved by constructing media-based enterprise networks in terms of the co-exposure in news reports of stocks and mutual attentions among them. Our experiments based on CSI 300 listed firms show the significant comovements of stocks brought out by their behaviors in Web media. Furthermore, utilizing media based enterprise networks can help us identify the most influential firms which can stir up the stock markets.

Keywords: Social media, stock comovement, social network analysis.

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INTRODUCTION

Stock comovement, a covariant phenomenon that stocks have similar movement of prices, is crucial to market risk premium and capital cost, portfolio management, style investing and economic resource allocation (Roll, 1989; Han & Xiao, 2005; Chelley-Steeley, Lambertides, & Savva, 2013; Dong, Liu, Hu, & Zhang, 2013). It is also an important signal to understand the market crisis. Specifically, the higher the frequency of comovements, the higher opportunity of market collapse (Hutton, Marcus, & Tehranian, 2009).

Earlier studies focused on the stock comovement from the perspectives of fundamentals, such as firm size and market characteristics (Adler & Dumas, 1983; McQueen & Roley, 1993). This is supported by the Efficient Market Hypothesis (EMH) theory that states that a stock price is always driven by “unemotional” investors to equal the firm’s rational present value of expected future cash flows. However, recent behavioral finance studies have attributed the non-randomness of stock movements such as overreactions to unfavorable news to investors’ cognitive and emotional biases (Long, Shleifer, Summers, & Waldmann, 1990). Realizing such “irrational” investors, researchers have begun to study stock comovements from the view of investors’ preferences. For examples, Rashes and Li found that there was a highly abnormal positive correlation between the stock prices of firms with only similar names but nothing in common (Rashes, 2001; Li, Tang, & Liu, 2011). Kumar discovered that the mental activities and behaviors of investors contributed to stock comovement, especially, the preference difference between retail investors and institutional investors would lead to different return comovements (Kumar & Lee, 2006). This phenomenon is regarded as the habitat-based comovement suggested by Barberis *et al.* (Barberis, Shleifer, & Wurgler, 2005).

Besides the perspectives of fundamentals and preferences, recent studies show that uneven information diffusion affects stock comovements as well (King & Wadhwani, 1990; Connolly & Wang, 2002). Li *et al.* pointed out that Web media plays an important role in affecting stock fluctuations as a powerful information diffusion intermediate (Li, Wang, & Li, 2014). Because of the easy accessibility of their public information for investors provided by Claessons and Yaleh (2012), Vijn (1994) found that listed firms in S&P 500 have a priority of price increase. Liu *et al.* showed the comovements of the stocks which have a strong connection among enterprise blogs (Liu, Wu, Li, & Li, 2015).

In this article, we follow the track of information diffusion to study stock comovements occurred by their behaviors in Web information. Especially, we first construct media-based enterprise networks in terms of the behaviors of listed firms in public media and study the stock comovements, in particular, the wave effect caused by influential firms, with the networks. Our unique contributions include:

- To the knowledge of our best, it is the first attempt to study stock comovements utilizing the graph topology of relevant stocks which provides a visual approach to understand the complicated mechanism of stock comovements.
- This is achieved by constructing media-based enterprise networks in terms of the co-exposure in news reports of stocks and mutual attentions among different listed firms.

- The media-based networks provide a systematical way to study the stock comovements from the perspective of information diffusion. We provide a concrete example of utilizing the networks to find the influential firms and study their wave effect in stock markets.

SYSTEM DESIGN

In this work, we propose a framework to study stock comovements from the perspective of information diffusion as shown in Figure 1.

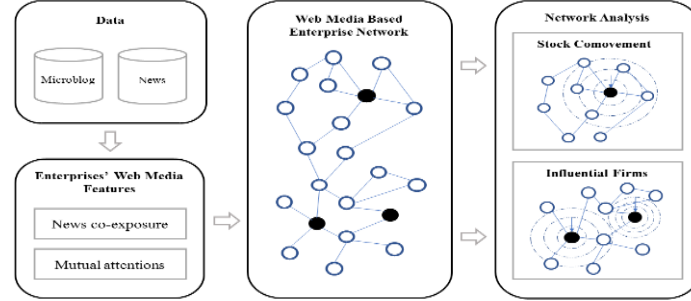


Figure 1: System overview

In particular, we first extract media behaviors of listed firms and construct media-based enterprise networks in terms of these behaviors. Stock comovements can be studied by the topological analysis of the networks. In the rest of the section, we provide the details of constructing media-based enterprise networks.

Enterprise Network Construction

In this section, we present the way to construct enterprise networks. Let suppose there is a list of enterprises $T: \{C_1, C_2, \dots, C_N\}$, we built the network by using two characteristics of web media, that is, the mutual attention information of enterprises on Microblogs and co-exposure of enterprises in news reports.

Constructing the enterprise network based on mutual attention on microblogs

In this study, the mutual attention of enterprises on Microblogs refers to the number of followings and followers of official Microblog accounts for each enterprise from CSI 300 Index. It is denoted as D_{ij} , $j=1, 2, \dots, N$, $j \neq i$, where D_{ij} is the followed situation of enterprise C_i by the other firm C_j . If C_i is followed by C_j , D_{ij} is set to 1, otherwise, it is 0. Here, we use Weibo as our microblog website, which is one of the largest microblog platforms in China.

To build the enterprise network based on mutual attentions, we first check whether an enterprise in the CSI 300 list T has the official Weibo account. If not, remove the enterprise from list T. For firm C_i in the list T, we maintain a sub-list $T_i: \{C_{i1}, \dots, C_{im}\}$ which indicates the connection between C_i and C_j if D_{ij} is 1. Combining the sub-lists of the firms in list T, we can obtain the enterprise network based on mutual attentions on Weibo.

Constructing the enterprise network based on co-exposures of firms in news reports.

Here, each node is the firms in list T, the connection of between node C_i and C_j is determined by the number of news (M_{ij}) have the information about both firm C_i and C_j . For each C_i , we establish a set of pairs composed by the connected enterprise C_j of C_i and M_{ij} as follow: $S_i: \{ \langle C_1, M_{i1} \rangle, \langle C_2, M_{i2} \rangle, \dots, \langle C_j, M_{ij} \rangle, \dots, \langle C_N, M_{iN} \rangle \}$. Then, we perform the normalization and redundancy processing for M_{ij} of each pair and select higher value of normalized M_{ij} to establish a strong connected enterprise list of C_i denoted as $S_{i,m}: \{ n \leq (N-1) \mid C_{i+1}, C_{i+2}, \dots, C_{ij}, \dots, C_{iN} \}$. Note that, we normalized the value of M_{ij} and screen out weak connection of firms in term of M_{ij} because there are large number of news for the joint report of two related firms.

Measures to Detect Stock Comovements

With the obtained enterprise networks, we can examine whether it reveals the media-based stock comovements by calculating the correlation coefficients of firms in terms of their stock prices. If firms with strong relationships determined by the topology of the network also show strong correlations by prices, it supports that the existence of media-based stock comovements.

¹ There are 221 listed firms in CSI-300 Index having official Microblog accounts.

For this purpose, we calculate two different correlation coefficients. That is, the average correlation coefficient of a node with its directly connected nodes (ACC), and the average indiscriminate correlation coefficient of a node with all other connected or unconnected nodes (AICC). Note that, If the ACC of a node is high, it indicates that the corresponding firm has a high probability of having media-based comovements with its connected firms in the constructed enterprise network. If the ACC is larger than the AICC for a target firm, it further proves that the existence of media-based comovements. In the rest of this part, we present the details of calculating these coefficients.

In this study, the correlation coefficient between C_i and C_j is calculated as follows:

$$\rho_{C_i C_j} = \frac{\text{Cov}(P_{C_i}, P_{C_j})}{\sqrt{\text{Var}(P_{C_i})\text{Var}(P_{C_j})}} = \frac{\sum (P_{C_i} - \bar{P}_i)(P_{C_j} - \bar{P}_j)}{\sqrt{\sum (P_{C_i} - \bar{P}_i)^2 \sum (P_{C_j} - \bar{P}_j)^2}} \quad (1)$$

where, $P_i: \{P_{i1}, P_{i2}, \dots, P_{i2}\}$ is the daily close prices of C_i between period t_1 and t_2 . The ACC of node C_i is defined as

$$ACC_{C_i} = \frac{\sum_{j=1}^n \rho_{C_i C_j}}{n} \quad (2)$$

where, C_j belongs the nodes that C_i has direct connetions in the network, n is the total number of these connected nodes. The AICC of C_i can be calculated as

$$AICC_{C_i} = \frac{\sum_{j=1, j \neq i}^N \rho_{C_i C_j}}{N-1} \quad (3)$$

Thus, the average of the ACC of all connected nodes (EACC) can be obtained as:

$$EACC = \frac{\sum_{i=1}^N ACC_{C_i}}{N} \quad (4)$$

Similarly, the average of the AICC of all connected and unconnected nodes (EAICC) can be obtained as:

$$EAICC = \frac{\sum_{i=1}^N AICC_{C_i}}{N} \quad (5)$$

If EACC is larger than EAICC, it indicates the comovements of firms in the media-based enterprise networks.

The topology of the enterprise networks provides a way to study the strength of comovements in terms of the relationship among firms by their behaviors in public media. For example, we can discover the comovement of between a node and its neighbors in different layers. As shown in Figure 2, we define the nodes B, C, D as the first layer of node A which have direct connections by mutual attentions in microblogs or co-exposure in news reports. The second layer of node A consists of nodes E, F, G, I, J, and H, which have indirect connections with node A but have direct links with the nodes in the first layer of node A. Such topology is useful to analyze the wave effect of certain nodes.

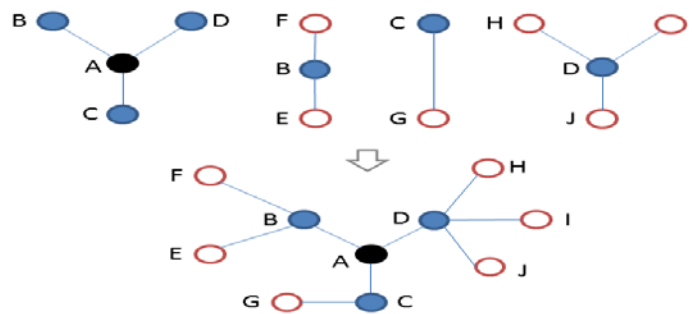


Figure 2: Network Layers

Measures for finding influential firms

Once the correlation coefficients show the existence of media-based comovements, we can infer the most influential firms in the networks and study their wave effect. To find out the influential firms, we adopt three measurements to determine their authority

in the networks. That is, individual centrality, closeness centrality, and betweenness centrality. Table 1 shows the detailed definition of these measures. In particular,

Individual centrality

The individual centrality of an enterprise is denoted as the number of the lines which directly connect with other nodes by mutual attentions or co-exposure in news. Let x_{ij} denotes the connection between nodes C_i and C_j , the individual centrality of C_i is defined as

$$IC_i = \sum_{j=1}^n x_{ij} / n \quad (8)$$

where, n is the maximum degree of any node C_i in the network which denotes the maximum number of the lines directly connected nodes with node C_i . The higher the individual centrality, the greater the impact of the node. As shown in Table 1, NrmDegree, denoted by (8), is the standardized individual centrality of C_i . NrmDegree is used to compare the centrality of the nodes in the same network. Degree means the absolute individual centrality which actually equals to the sum of x_{ij} . And Share denotes the proportion of the individual centrality of a corresponding node in the whole network, which is used to characterize the core of any point in the entire network.

Closeness centrality

The closeness centrality of a node is a measure of centrality in a network, calculated as the sum of the length of the shortest paths between the node and all other nodes in the graph. Thus the more central a node is, the closer it is to all other nodes. Let $g(C_i, C_j)$ be the number of shortest paths between nodes. $g(C_i, C_j)^{-1}$ is used to measure the value of the closeness centrality of one node. The normalized closeness centrality is calculated as follow

$$CC_i = n / \sum_{j=1}^n g(C_i, C_j) \quad (10)$$

where, n^{-1} is the maximum value of the closeness centrality of a target node which is the core node in the network. The larger the closeness centrality of an enterprise, the faster the speed of spreading its price changes to other firms. Similarly, inCloseness in Table 1, which is denoted by (10), is the closeness extent between node C_i and the other directly connected nodes which are towards it. The outCloseness denotes the closeness extent of node C_i towards to others. The inFarness and outFarness denote the extent that node C_i is far away from other directly connected nodes.

Betweenness centrality

The betweenness centrality of an enterprise refers to the degree to which nodes in the network participate in the connection path of the remaining nodes. It calculated by

$$BC_i = \frac{E_{jk}(C_i) / E_{jk}}{n(n-1) / 2} \quad (11)$$

Where, E_{jk} is the number of shortest paths between node j and k , $E_{jk}(C_i)$ is the number of paths that the node i on the shortest paths between node j and k . The higher the betweenness centrality is, the more often this enterprise becomes the betweenness of the remaining two connected enterprises, and the more vulnerable this enterprise is impacted by stock comovement. It also indicates the importance of the node because a part of stock comovement will spread out via this node. In Table 1, Betweenness and nBetweenness are the measures of the betweenness centrality. Betweenness is the absolute betweenness centrality and nBetweenness are the standardized betweenness centrality which is denoted by (11).

Table 1: The Evaluation criterias about centrality analysis

Measures		Explanation
Individual centrality	Degree	Absolute individual centrality
	NrmDegree	Relative individual centrality
	Share	The proportion of a target node in network
Closeness centrality	inFarness	Farness extent of the in-degree for one node
	outFarness	Farness extent of the out-degree for one node
	inCloseness	Closeness extent of the in-degree for one node
	outCloseness	Closeness extent of the out-degree for one node

Betweenness centrality	Betweenness	Absolute betweenness centrality
	nBetweenness	Relative betweenness centrality

EXPERIMENTAL EVALUATION

Dataset

In this study, we made a focused web crawler to collect the microblogs and news articles. In particular, we took the 300 listed firms from CSI 300 index, which is a capitalization-weighted stock market index designed to replicate the performance of 300 stocks traded in the Shanghai and Shenzhen stock exchanges. Their news reports are crawled from www.eastmoney.com which is one of the largest financial information website in China., and the mutual attentions among these listed firm are extracted from Weibo.com. Weibo is a Chinese microblogging website. Akin to a hybrid of sites Facebook and Twitter, it is one of the most popular sites in China, in use by well over 30% of Internet users. The China Stock Market & Accounting Research (CSMAR) database is used to obtain stock prices. More details can be referred to Table 2.

Table 2: Data Information

<i>Data</i>	<i>Source</i>	<i>Amount</i>	<i>Date</i>
Enterprises	CSI 300	300	2015.6.1
Stock pricea	CSMAR	120,000	2014.1.1 - 2014.12.31
News co-exposure	eastmoney.com	44,536	2014.1.1 - 2014.12.31
Mutual attention	weibo.com	52,664	2014.1.1 - 2014.12.31

^a Stock price is the daily close price of individual stock

The Enterprise Network Based on Mutual Attentions in Microblogs

Stock comovement

As shown in Figure 3, with the enterprise network based on mutual attentions, we can calculate the average correlation coefficient of a node with its directly connected nodes (ACC) and the average indiscriminate correlation coefficient of a node with all other connected or unconnected nodes (AICC). Comparing the distribution of ACC with that of AICC, 29 firms have strong connections with the coefficient more than 0.8. In addition, the EACC is larger than EAICC in the enterprise network based on mutual attentions. This further proves that firms sharing mutual attentions in microblogs tend to have stock comovements in prices.

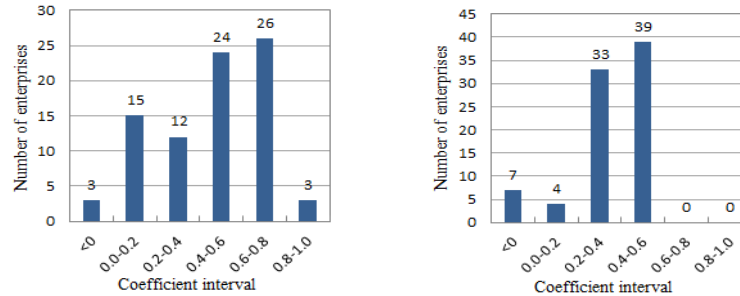


Figure 3: Coefficient Distribution in The Enterprise Network Based on Mutual Attentions

Finding influential firms

Figure 4 shows the snapshot of the enterprise network based on mutual attentions.

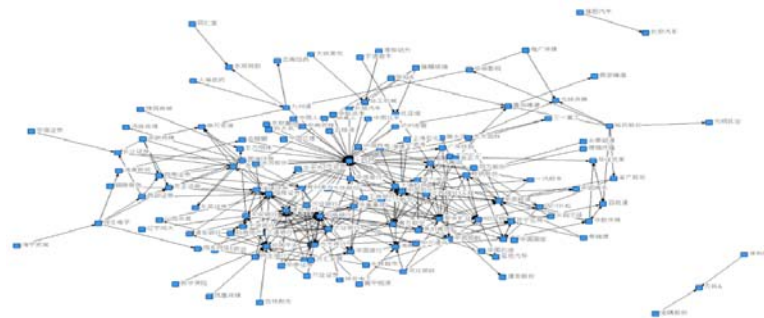


Figure 4 Snapshot of the enterprise network based on mutual attentions

By calculating the individual centrality, closeness centrality and betweenness centrality of each node in this network, we can find the most influential enterprises (authorities) in the network. Table 3, 4 and 5 show the results of these measures, respectively.

Table 3: Individual centrality of Enterprise Network Analysis Results Based on Web Mutual Attention

<i>Enterprise</i>	<i>Degree</i>	<i>NrmDegree</i>	<i>Share</i>
People.cn	49.000	36.296	0.075
CMB	27.000	20.000	0.041
Sinopec Group	23.000	17.037	0.035
CMS	16.000	11.852	0.025
ABC	16.000	11.852	0.025
Zijin Mining	14.000	10.370	0.021
China Unicom	13.000	9.630	0.020
Pingan Insurance	12.000	8.889	0.018
Kweichow Moutai	12.000	8.889	0.018
CCB	11.000	8.148	0.017

Table 4: Closeness Centrality of Enterprise Network Analysis Results Based on Weibo Mutual Attention

<i>Enterprise</i>	<i>In-Farness</i>	<i>Out-Farness</i>	<i>inCloseness</i>	<i>outCloseness</i>
SWHY Security	3185.000	18360.000	4.239	0.735
People.cn	3322.000	10079.000	4.064	1.339
CMB	3405.000	9983.000	3.965	1.352
Sany Group	3408.000	18360.000	3.961	0.735
CJ Securities	3415.000	18360.000	3.953	0.735
CITS	3417.000	18360.000	3.951	0.735
CS Air	3420.000	9967.000	3.947	1.354
GS Railway	3433.000	10017.000	3.932	1.348
Bank of China	3436.000	18360.000	3.929	0.735
Sinopec Group	3440.000	9942.000	3.924	1.358

Table 5: Betweenness Centrality of Enterprise Network Analysis Results Based on Weibo Mutual Attention

<i>Enterprise</i>	<i>Betweenness</i>	<i>nBetweenness</i>
Sinopec Group	2375.623	13.132
CS Air	2077.621	11.485
CMS	1776.716	9.822
People.cn	1629.961	9.010
Guangshen Railway	1580.961	8.739
CMB	872.640	4.824
ABC	816.772	4.515
China Unicom	767.896	4.245
Kweichow Moutai	727.549	4.022
CCB	681.857	3.769

In Table 3, People's Daily Online (People.cn) has the highest individual centrality, which is tightly followed by several enterprises in banking and energy industrial field including China Merchants Bank (CMB), Sinopec Group, China Merchants Securities (CMS), and Agricultural Bank of China (ABC). Top companies in Table 3 indicate that their price fluctuations have the most influential power to shake the prices of others. In Table 4, the enterprises in banking, securities, and transportation generally have a high closeness centrality. This means that the path of these enterprises to the rest of the nodes connected with them in the network is generally short, and their price fluctuations can quickly spread over in this network. Table 5 shows that, the enterprises, such as Sinopec Group, China Southern Airlines Company Limited (CS Air), CMS, People.cn, Guangshen Rail-way, have high betweenness centralities, which indicates such enterprises tend to become the intermediate nodes to participate in the stock comovement of other enterprises. Controlling the fluctuations of such stock prices in time helps to limit the spread of stock fluctuations.

The Enterprise Network Based on Co-exposure in News

Analysis of stock comovement

Different with the network based on mutual attentions where the connection is indicated by Boolean value 0 or 1, the connections in news based network are weighted by the number of news articles which have the content about both firms (nodes). To construct the enterprise network, we set a threshold and if the number of common news is large than the threshold, we set the edge of these two firms to 1, otherwise 0. Figure 5 shows the relationship between the threshold for the normalized news numbers and the EACC of the network. It shows that the optimal threshold is 0.6. Therefore, we can construct an enterprise network based on news co-exposure as shown in Figure 6.

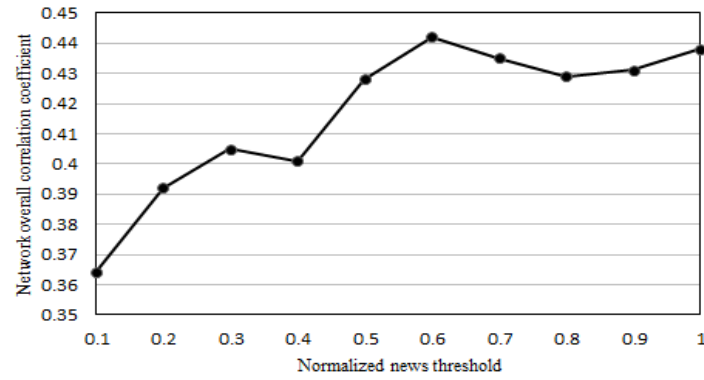


Figure 5: Correlation Coefficient under Different Thresholds

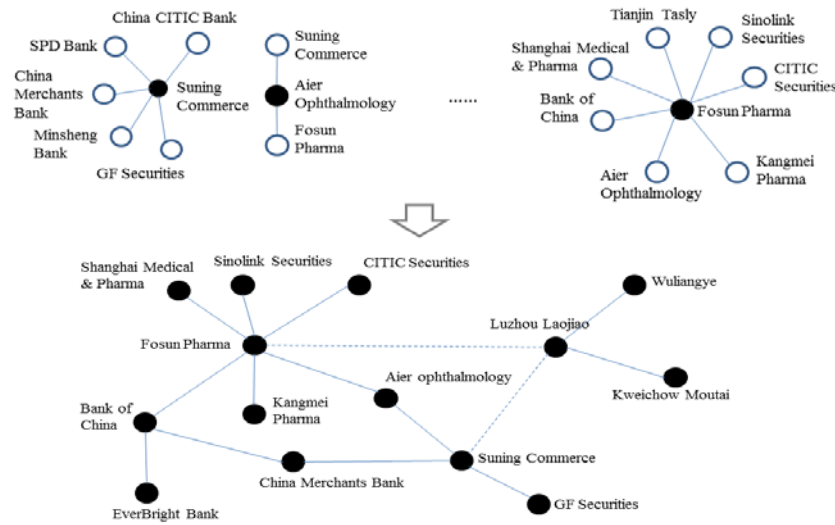


Figure 6: Snapshot of The Enterprise Network Based on Co-exposure News

In Figure 7, we can observe that the average correlation coefficient of nodes with their directly connected nodes (ACCs) are mainly distributed between 0.4 and 0.8, and 5 firms are larger than 0.8. Since the EACC is larger than EAICC in this enterprise network, it shows that firms with common news reports tend to have stock comovements in prices.

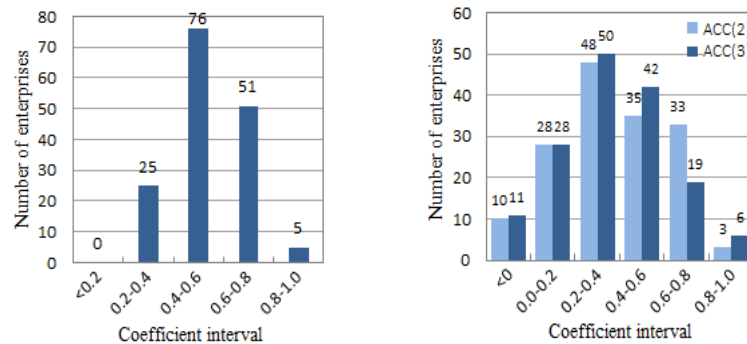


Figure 7: Coefficient Distribution in The Enterprise Network Based Co-exposure News in Terms of Different Layers

Here, we also examine the news influence in different layers in the network. Figure 7 also shows the coefficient distribution of the second and third layers. It can be observed that the ACCs of some firms shift from the range of high values to the lower value range. In addition, the EACC of the first layer is 0.424, the EACC of the second layer is 0.357, and the EACC of the third layer is 0.328. Therefore, we can conclude that the comovements of firms with direct common news reports are significant than the firms with indirect connections in news reports.

Finding influential firms

Similarly, by calculating the individual centrality, closeness centrality and betweenness centrality of each node in this network,

we can find the most influential enterprises (authorities) in the network. In our result, the firms in the industrial field of banking and securities, such as CITIC Securities, Guangfa Securities, China CITIC Bank, Bank of Nanjing, Industrial Securities, China Minsheng Bank, typically has a higher individual centrality. For closeness centrality, the enterprises, such as Bank of Nanjing, China International Marine Containers (CIMC), Western Mining, Sealand Securities, Shanghai Airport Authority, Kingenta, Shanghai RAAS, Zhongheng Group, Chuantou energy, from the industry of energy and transportation, and banking and securities tend to have high values. This indicates these firms have short paths to other firms and hence can spread their fluctuations to other more quickly. In addition, the companies, such as CITIC Securities, Guangfa Securities, SDIC Huajing Power Holdings, Shanghai Pharma, China Minmetals Rare Earth, Zheneng Electric Power Co., Ltd, China Changan Automobile Group, Qinghai Salt Lake Industry Group, Yanghe Brewery Joint-Stock Co., Ltd, Suming Commerce Group Co., Ltd, have higher betweenness centrality, which shows these companies tend to become the intermediate nodes to participate in the stock comovement of other enterprises. Controlling the fluctuations of these firms helps to limit the spread of stock fluctuations.

CONCLUSION

Stock return comovement analysis refers to identifying homogeneous groups of stocks that have similar movement of returns. Such an analysis is very important for managing investment portfolios, economic resources allocation, and market risk controlling. In this study, we focused on the CSI 300 index listed firms and constructed two media-based enterprise networks in terms of mutual attentions of enterprises on Weibo and the co-exposure in news reports for stock comovement analysis. In our large-scale experimental evaluation, we first prove the existence of media-based stock movements and utilize our media-based enterprise networks to find the most influential firms which are capable of leading the stock comovement in stock markets. We also found that the enterprise from the industry of banking, securities, energy, and transportation, tends to have the most influential power in the media-based networks. Keeping a watchful eye on the relevant information about these stocks would help understand or even predict the stock comovement of their connected enterprises. The media-based enterprise networks provide an innovative way to study stock comovements from the perspective of information diffusion. However, its efficiency for the entire markets rather than CSI 300 is yet to be explored in the near future.

ACKNOWLEDGEMENT

This work has been supported by grants awarded to Dr. Qing Li from National Natural Science Foundation of China (NSFC) (71671141, 71401139), and Fundamental Research Funds for the Central Universities (JBK 171113, JBK 170505, JBK 151128, JBK120505).

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