Influence network in the Chinese stock market

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Abstract. In a stock market, the price fluctuations are interactive, that is, one listed company can influence others. In this paper, we seek to study the influence relationships among listed companies by constructing a directed network on the basis of the Chinese stock market. This influence network shows distinct topological properties. In particular, a few large companies that can lead the tendency of the stock market are recognized. Furthermore, by analyzing the subnetworks of listed companies distributed in several significant economic sectors, it is found that the influence relationships are totally different from one economic sector to another, of which three types of connectivity as well as hub-like listed companies are identified. In addition, the rankings of listed companies obtained from the centrality metrics of the influence network are compared with those according to the assets, which gives inspiration to uncover and understand the importance of listed companies on the stock market. These empirical results are meaningful in providing these topological properties of the Chinese stock market and economic sectors as well as revealing the interactive influence relationships among listed companies.

Keywords: correlation functions (theory), models of financial markets, socio-economic networks
In modern portfolio theory, risk diversification is the most essential issue, which involves the understanding of clustering behavior and risk contagion of the assets in a portfolio. Thus, in a stock market, the price fluctuation of a listed company’s assets (i.e. stocks) is parallel to others or interactively influenced by others. The widely used cross-correlation analysis is an important measurement to investigate the interactive relationships between pairs of stocks for understanding the dynamic mechanics in a complex economic system. For example, the random matrix theory (RMT) suggests the eigenvalues and corresponding eigenvectors of the cross-correlation matrix of price fluctuations are relevant to clustering behavior and economic sector division (or taxonomy) of stocks [1–4]. Meanwhile, with the development of complex network theory, diverse cross-correlation-based stock networks are proposed to describe the interactive relationship, such as minimum spanning tree (MST) [5–8], planar maximally filtered graph (PMFG) [9], and threshold networks (TN) [10–12], etc. In particular, the clustering behavior of stocks can be well associated with the communities scratched from these stock networks via complex network measurement.

In order to evaluate risk contagion, a lot of work has been devoted to analyzing the influence relationships from a directed network perspective. Kenett et al [10] introduced
the measurement of partial correlation to construct TN and PMFG of listed companies and uncover the dominating ones in a stock market. The Engle-Granger method [13] is an alternative way to obtain the asymmetric influences (i.e. Granger causality) among listed companies. For example, Yang et al [14] constructed a directed cointegration network of global stock markets based on the Engle–Granger cointegration test, and presented ranking analysis of nodes to distinguish their importance. Also, time-dependent cross-correlation [15–17] is applied to determine the linking direction between a pair of listed companies due to the time shift of maximum correlation. If the time shift is non-zero, the ‘pulling’ effect is assumed to exist in these listed companies.

As an important emerging market, the Chinese stock market possesses unique properties, such as stronger cross-correlations and less market efficiency [18]. There are few works involving the unidirectional influence relationship [19, 20]. However, these results are obtained based on daily stock returns, and thus may be debatable under the consideration of an efficient market. In this paper, we mainly focus on the risk contagion in the Chinese stock market, by constructing a directed influence network on the basis of a time series of minute-by-minute price fluctuations with the time-dependent cross-correlation method, which is well behaved in the American stock market [15]. Unlike in previous literature, we analyzed not only the global topological structure, but the subnetworks of a few significant economic sectors with the aim of exploring the unique economic structure of China. Empirical results reveal three types of connectivity involving the intra-sector's influence relationship. We compare several measurements of node centrality to find out available characterization of the importance of listed companies in this influence network. The findings provide intriguing information about the topological properties of the Chinese stock market and give an important hint about risk contagion in portfolio management.

2. Materials and methods

2.1. Data sets

The data set consists of \( N = 779 \) stocks (i.e. listed companies) trading on the Shanghai Stock Exchange (SSE). These stocks belong to 18 economic sectors, of which the name and size are shown in table 1. The price fluctuations which are sampled with minute frequency, can quickly respond to interactive influence relationships among stocks. The duration is the whole fiscal year of 2010, which included 242 trading days with 4 h working time per day. For the price fluctuation of each stock, its return at time scale \( \Delta t \) is obtained by

\[
 r_{\Delta t}(t) = \frac{\ln[p(t)] - \ln[p(t-\Delta t)]}{\ln[p(t-\Delta t)]}. \tag{1}
\]

We set \( \Delta t = 1 \) min because larger \( \Delta t \) may smear out the maximum and \( r_{\Delta t}(t) \) is denoted by \( r(t) \) for simplicity.

2.2. Time-dependent cross-correlation

To evaluate the interactive influence relationships among stocks, their time-dependent cross-correlations are calculated. Within a trading day \( T \), the correlation between stocks
Table 1. Number of stocks from each economic sector in the data set.

| Sector                        | Number | Sector          | Number |
|-------------------------------|--------|-----------------|--------|
| Finance                       | 22     | Construction    | 23     |
| Mining Industry               | 30     | Energy          | 42     |
| Manufacturing                 | 418    | Real Estate     | 58     |
| Wholesale & Retail            | 59     | Transportation  | 47     |
| Lodging & Catering Service   | 3      | Agriculture     | 14     |
| Information Technology        | 20     | Other Service   | 1      |
| Lease & Business Service      | 8      | Utility         | 2      |
| Science & Technology Service  | 1      | Healthcare      | 1      |
| Public Management             | 25     | Entertainment   | 5      |

Figure 1. The time-dependent cross-correlation between stocks ACGK and ZSYH as a function of time shift $\tau$. The maximum value appears at $\tau_{\text{max}}(i,j) = -1$, indicating that stock ZSYH influences stock ACGK in their price fluctuations. All the abbreviations for companies are listed in table A1 of the appendix.

$i$ and $j$ can be calculated as

$$C_{i,j}^T(\tau) = \frac{\langle r_i(t)r_j(t+\tau) \rangle - \langle r_i(t) \rangle \langle r_j(t+\tau) \rangle}{\sigma_i \sigma_j},$$

where $\sigma_i$ and $\sigma_j$ are the standard deviation of $r_i$ and $r_j$ and the parameter $\tau$ in $C_{i,j}^T(\tau)$ is the time shift. Changing $T$, the $C_{i,j}^T(\tau)$ are then averaged over the trading days to filter the dairy effect \[21–23\], and the mean value is denoted by $C_{i,j}(\tau)$.

With various values of $\tau \in [-100, 100]$, the corresponding $C_{i,j}(\tau)$ are then obtained, of which the maximal value is selected, denoted as $C_{\text{max}}(i,j)$, and its related time shift as $\tau_{\text{max}}(i,j)$. For example, as shown in figure 1, $C_{i,j}(\tau)$ between stocks $i$ (ACGK) and $j$ (ZSYH) changes with various $\tau$, where $C_{\text{max}}(i,j) = 0.07$ is obtained at $\tau_{\text{max}}(i,j) = -1$. It suggests that stock $j$ influences stock $i$ in their price fluctuations. Besides, to differentiate from $C_{\text{max}}(i,j)$ to noise, the parameter $R(i,j)$ is measured as the ratio of $C_{\text{max}}(i,j)$ and the noise strength defined as the variance of all correlation values with time shift from the peak larger than 10 min because the largest peak width is 6 min.

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2.3. Influence network construction

With time-dependent cross-correlations, the influence relationships of all pairs of stocks can be quantitatively measured. To construct a directed network describing influence relationships, we adopt the method proposed in [15], which emphasizes that three parameters $C_{\text{max}}(i,j)$, $|\tau_{\text{max}}(i,j)|$, and $R(i,j)$ should exceed certain threshold values simultaneously if the directed connection between stocks $i$ and $j$ exists. It is obvious that the topological structure of the influence network has a direct relevance to these thresholds. Figure 2 shows the size of the largest component as a function of $C_{\text{max}}$ and $R$, respectively. One can see that the size of the largest component decreases whenever the threshold value of $C_{\text{max}}$ or $R$ is improved, because more links are filtered. And in both cases, there is a critical point when the full-connected network decomposes and the size of the largest component decreases rapidly. Based on the percolation-based method [11,12], the value of the phase transition point from full connection to isolated components is $C_{\text{max}} \geq 0.04$ and $R \geq 4$. Moreover, $|\tau_{\text{max}}(i,j)| \geq 1$ is required.

In the influence network, link $L_{i,j}$ between stocks $i$ and $j$ is unidirectional, determined by the sign of $\tau_{\text{max}}(i,j)$. If $\tau_{\text{max}}(i,j) < 0$, the current price of stock $i$ is affected by the previous one of stock $j$, denoting the link direction from $i$ to $j$. Otherwise, the link is directed to $i$ from $j$ if $\tau_{\text{max}}(i,j) > 0$. It should be pointed out that, in our network, a directed link is set from $i$ to $j$ if $j$ influences $i$. However, the reverse is also a feasible choice. When $\tau_{\text{max}}(i,j) = 0$ (i.e. the equal time cross-correlation), we recognize the mutual influence as an external effect. The price fluctuations of two stocks may be induced by the trend of the stock market or environmental variation in the economic sector. Therefore, in this case, stocks $i$ and $j$ aren’t connected.

In order to further get rid of the noises that the maximum of the correlation is attributed to occasional large values rather than a real association, the fiscal year is divided into three periods. In each period the $C_{i,j}(\tau)$ is calculated, according to which an adjacent matrix is established, and only those links that exist in all three periods are considered in the network to ensure the robustness of the result.

Figure 2. The size of the largest component of the influence network versus various thresholds of (a) $C_{\text{max}}$ with $R = 4$ and (b) $R$ with $C_{\text{max}} = 0.039$. 

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Figure 3. Distributions of in-degrees (black squares) and out-degrees (red solid circles) of the influence network. The fat tail both in the in-degree and out-degree distributions suggests that there are hub-like nodes that strongly influence others.

Table 2. Top-10 companies with the highest in-degrees.

| Sector        | Company | In-degree | Sector    | Company | In-degree |
|---------------|---------|-----------|-----------|---------|-----------|
| Mining Industry | ZGSY    | 616       | Finance   | ZGTB    | 594       |
| Finance       | ZSYH    | 585       | Finance   | JTYH    | 580       |
| Finance       | HXYH    | 578       | Finance   | ZGRS    | 551       |
| Finance       | PFYH    | 542       | Mining Industry | SHE    | 538       |
| Finance       | XYYYH   | 538       | Finance   | BJYH    | 511       |

3. Empirical results

3.1. Analysis of the influence network

The resulting influence network has dense edges, with the average degree high to 34.84. Figure 3 shows the distributions of in-degree and out-degree, respectively. Both of them approximately decay in an exponential way when the degree $k$ is at a small scale. Nevertheless, the fat tail both in the in-degree and out-degree distributions reveals there are some hub-like nodes in the influence network. In other words, a few huge stocks can strongly influence, or even control the trend of the Chinese stock market. In table 2, it shows that the top-10 stocks with the highest in-degree are mainly distributed in the Mining Industry and Finance sectors, and affect almost the whole stock market. For example, ZGSY, the largest listed company in China, influences more than 600 stocks in all economic sectors, as shown in figure 4. However, it is interesting that the majority of all the economic sectors are influenced, except for that of finance, but only a fraction of 3/22 are linked to ZGSY.

In addition, we pay attention to the interactive influence relationships among stocks with top-50 in-degree. Figure 5 shows that there are only 12 directed connections, which...
Figure 4. A visualization of ZGSY’s influence on 616 stocks distributed across 17 economic sectors. The thickness of the edges denotes the number of stocks linked to ZGSY in a certain economic sector. The proportions in 18 economic sectors are 13/14 in Agriculture, 21/30 in the Mining Industry, 359/418 in Manufacturing, 32/42 in Energy, 19/23 in Construction, 47/59 in Wholesale & Retail, 30/47 in Transportation, 11/13 in Service (including 4 types), 16/20 in Information Technology, 39/58 in Real Estate, 4/5 in Entertainment, 2/2 in Utility, 1/1 in Healthcare, 18/25 in Public Management.

Figure 5. The connectivity among the top 50 companies with the highest in-degrees. Few edges existed in this core-like influence network. Suggests that these stocks are relatively independent, that is, their price fluctuations are parallel to each other. Nevertheless, ZGSY still plays an important role in this core as its in-degree is 6, equaling half of the total connections.

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Furthermore, we have noticed that those nodes with high in-degrees (namely more influence) have high capitalization. The positive correlation between influence and capitalization has been studied by Lo and MacKinlay [24] with weekly return data. To observe this effect in high-frequency return data, we calculate the difference between the assets of the two connected nodes $i \rightarrow j$ as \[ \Delta L_{ij} = L_j - L_i \] (3)

where $L$ represents equity capital, obtained by averaging equity capitals from the beginning and the end of 2010. Figure 6 shows the distribution of all $\Delta L$ values for the whole network. It can be found that the peak locates at $\Delta L > 0$ rather than zero, and the shape of the peak is asymmetric, as the right side is fatter. These properties clarify that smaller capitalized listed companies tend to be affected by bigger capitalized listed companies but not vice versa, which is in accordance with previous studies, thus confirming the validity of this influence network. Take note of the inset, where the right tail tends to be growing, which is related to the fat tail of in-degree distribution.

In the above discussion, we are concerned with the most influential stocks. In addition, we analyze the most influenced stocks represented by higher out-degree to better understand the influence network. As shown in table 3 the top-10 stocks with the highest out-degree are displayed, along with their economic sectors. One can see that they are completely different from those most influential ones. Compared to table 2, their values of out-degree are much lower than that of in-degree, which suggests that these stocks are influenced by only a portion of the other stocks, and these most influenced stocks are distributed across more diverse economic sectors, such as Manufacturing (5), Real Estate (2), Energy (1), Transportation (1), and Wholesale & Retail (1). Nevertheless, it is easy to understand the difference because on the stock market these influential stocks are able to pull others via a cascading effect of network but those influenced stocks aren’t guaranteed to be attracted by all the others.
3.2. Analysis of subnetworks in economic sectors

We have given an overview of the investigation of the influence network at whole scale. However, information of interactive influence relationships in intra-sectors needs to be probed. Based on the taxonomy of the Chinese stock market, we obtain a series of subnetworks from the whole influence network. Figure 7 shows six significant economic sectors, such as Construction, Wholesale & Retail, Finance, Mining Industry, Energy, and Real Estate. It can be found that the connection configurations are different from each other, on the basis of which the sectors can be classified into three types:

1. There are few edges inside the sector, but hub nodes are apparent. For instance, in the sector of Construction (figure 7(a)), there are two key nodes of the highest in-degrees, corresponding to the industry heavyweights, ZGTJ and ZGZT. The same properties can be found in the Energy sector. As shown in figure 7(b), CJDL is the largest listed company in the Energy sector, and SCGF is the second largest. The most susceptible vertex is GDDL.

2. The stocks rarely interact with others in the same sector, and there are no apparent hub-like nodes as the distribution of in-degrees is approximately homogeneous, such as Finance (figure 7(c)) and Wholesale & Retail (figure 7(d)). In figure 7(d), the relatively important nodes, denoted by the red circle, is WKFZ (providing metals and metallurgical raw materials). Two other susceptible nodes, *STSS and BHC, are also tagged. Although, in the global network analyzed above, eight of the top-10 in-degree nodes are financial stocks, which can affect a large quantity of nodes in the whole network, they barely influence each other. Furthermore, it is interesting that the Finance sector is insensitive to other sectors, yet it impacts all the other sectors.

3. The intra-sector influence relationships are much more considerable compared with the first two classes, and the industry giants can be easily observed from these subnetworks. In figure 7(e), the Mining industry has four huge listed companies, ZGSY, ZGSH, SHE, and XBKY. In addition, the two observed giants are BLDC and JDJT in the Real Estate sector (figure 7(f)).

3.3. Analysis of node centrality

It is a critical problem to evaluate the node importance in a directed network, and dozens of centrality metrics have been proposed, such as Betweenness Centrality (BC) [26, 27],

| Sector      | Company | Out-degree | Sector     | Company | Out-degree |
|-------------|---------|------------|------------|---------|------------|
| Manufacturing | SBGX    | 223        | Real Estate | ZFGF    | 220        |
| Manufacturing | BXGF    | 210        | Manufacturing | SHSC    | 183        |
| Energy      | GDDL    | 182        | Transportation | TJHY    | 178        |
| Manufacturing | MYL     | 168        | Wholesale & Retail | BHC    | 167        |
| Manufacturing | FRYY    | 167        | Real Estate | SQF     | 162        |
Figure 7. The subnetwork for six economic sectors of (a) Construction, (b) Energy, (c) Finance, (d) Wholesale & Retail, (e) Mining Industry, (f) Real Estate. The color and size of the solid circles correspond to the in-degrees. Three configuration are recognized: little connection with hub nodes (e.g. subfigures (a) and (b)); little connection and no hub nodes (e.g. subfigures (c) and (d)); much more intra-connection with hub nodes (e.g. subfigures (e) and (f)). Note that the most vulnerable nodes are marked in addition to the most essential ones.
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Table 4. Similarity between enterprise value (represented by Equity capital, Total assets and ROA) and node centrality measurements in terms of Kendall’s Tau coefficient.

|                | In-degree | PageRank | Eigenvector | Authority | Hub     | Betweenness |
|----------------|-----------|----------|-------------|-----------|---------|-------------|
| Equity         | 0.4072    | 0.4072   | 0.4108      | 0.4072    | 0.0767  | −0.1905     |
| Assets         | 0.3772    | 0.3773   | 0.3805      | 0.3773    | 0.0594  | −0.1938     |

Eigenvector Centrality (EC) [28], PageRank (PR) [29,30], Hub and Authority [31], which derive from diversely local topological properties of the influence network. However, it remains an unsolved issue which is the appropriate centrality measurement which can reflect the economic importance in a financial network. In this section, the ranking analysis of nodes based on these measurements is performed. On the other hand, the nodes are ranked due to the capitalization of the listed company, for which both total assets (including equity capital and liabilities) and equity capital are considered, denoted by assets and equity, respectively. The similarities of node ranking between assets and other centrality measurements are then calculated in terms of Kendall’s Tau (KT) coefficient [32], as well as equity. To keep our description self-contained, we briefly introduce the KT correlation. For two sequences \( \{x_i\} \) and \( \{y_i\}, i = 1, 2, ..., N \), the KT coefficient is given by

\[
\tau = \frac{2}{N(N-1)} \sum_{i<j} \text{sgn}(x_i-x_j)(y_i-y_j)
\]

Here \( \text{sgn}(x) = 1 \) for \( x > 0 \), while \( \text{sgn}(x) = -1 \) for \( x < 0 \), otherwise \( \text{sgn}(x) = 0 \). The result is shown in table 4.

One can see from table 4 that all the KT coefficients of equity are higher than those of assets. This is consistent with empirical observations that the influence of a listed company is positively related to its market capitalization in the equity market. More concretely, we discuss the correlation between each centrality measurement and equity (or asset) as follows.

First, it is not surprising that BC is in negative correlation with assets. BC of a vertex is defined as the frequency that is in the shortest path between any two other vertices. In the directed influence network, the shortest path between a pair of nodes is asymmetric. And the topological properties of the influence network have suggested that the important nodes are of large in-degrees and few out-degrees. Therefore, their BC values are very small, even zero for those with zero out-degrees.

Second, Hub and Authority are two parameters of HITS. For a node, its hub is determined by the authority of out-degree neighbors, while its authority is confirmed by the hub of in-degree neighbors. Thus, in the influence network, the authority of a node with larger assets is higher due to its greater number of in-degree neighbors, while its hub isn’t much larger than those of other nodes with fewer assets due to its smaller out-degree neighbors. On the other hand, most nodes with fewer assets connect collectively to those with larger assets, so no significant difference exists between their hub values. This explains the poor performance of the hub, and the better performance of authority.

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Third, both PR and EC can well indicate the node’s importance, suggested by the higher KT coefficient shown in Table 4. It is comprehensible because the two measurements have a similar idea that the importance of a node depends not only on the numbers but the importance of its in-degree neighbors. Although there are some arguments for the eigenvector of a directed network [28], it is practical for nodes with high in-degree, which is suitable for the influence network in this paper. Also of note is that the low value of the KT coefficient is concerned with the degree distribution. High in-degree nodes are of low out-degree, and the less important nodes are uniformly out-degree distributed.

4. Conclusion

In this paper, in order to investigate the interactively clustering behavior of listed companies induced by asymmetric market information, we have studied the influence network constructed from the time-dependent cross-correlation of stocks’ price fluctuations on the Chinese stock market. The empirical results can be concluded in three aspects.

From the distribution of the asset difference of all pairs of connected nodes, the good performance of the network is verified by revealing the influence relationships among listed companies. However, the network is found to display singular topological properties in the in-degree distribution, which can be attributed to the existence of hub-like listed companies that can influence the majority of the Chinese stock market. The out-degree distribution, on the other hand, is more diverse.

In addition, the intra-sector influence relationship is analyzed from subnetworks of a few economic sectors involved with the Chinese economy. The topological structure of the subnetworks differs among sectors in connectivity and hub nodes. Three configurations are identified: Few edges with apparent hub nodes, such as Construction; Few edges without hub nodes, such as Wholesale & Retail trades and Finance; Lots of links with apparent hub vertices, like the Mining Industry, Energy, and Real Estate. These results give important information about price fluctuations on the stock market, that is, they imply that the asymmetric market information transferring from one economic sector to the whole stock market behaves in diverse dynamic patterns. These may have significant applications for portfolio management and risk diversification.

In order to figure out which algorithms can characterize critical nodes in the influence network, we calculated the similarities between several centrality measurements and assets of listed companies, which is regarded as an indicator of their importance in the Chinese stock market. We found that the in-degree, PR, EC, as well as authority better characterize the importance of listed companies, while BC and hub fail to do so.

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Appendix

Table A1. Company names and symbols mentioned in the article.

| Label  | Symbol | Name                                           |
|-------|--------|------------------------------------------------|
| 600234 | *STSS<sup>b</sup> | Guanghe landscape Culture Communication |
| 600550 | *STTW | Baoding Tianwei Baobian Electric Co.            |
| 600207 | ACGK   | Henan Ancai Hi-tech Co.                        |
| 600643 | AJGF   | Shanghai Aj Corporation                         |
| 600721 | BHC    | Xinjiang Baihuacun Co.                         |
| 601169 | BJYH   | Bank Of Beijing Co.                            |
| 600048 | BLDC   | Poly Real Estate Group Co.                     |
| 60083 | BXGF | Guangdong Boxin Investing & Holdings Co.       |
| 600900 | CJDL | China Yangtze Power Co.                        |
| 600781 | FRYY | Furen Pharmaceutical Group Co.                 |
| 600310 | GDDL | Guangxi Guidong Electric Power Co.             |
| 600382 | GDMZ | Guangdong Mingzhu Group Co.                    |
| 600109 | GJZQ | Sinolink Securities Co.                        |
| 600015 | HXYH | Hua Xia Bank Co.                               |
| 600383 | JDJT | Gendale Corporation                            |
| 601328 | JTYH | Bank Of Communications Co.                     |
| 600993 | MYL | Mayinglong Pharmaceutical Group Stock Co.      |
| 601009 | NJYH | Bank Of Nanjing Co.                            |
| 600000 | PFYH | Shanghai Pudong Development Bank Co.           |
| 600604 | SBGX | Shanghai Shibei Hi-Tech Co.                    |
| 600008 | SCGF | Beijing Capital Co.                            |
| 600018 | SGJT | Shanghai International Port (Group) Co.        |
| 601088 | SHE | China Shenhua Energy Company                   |
| 600009 | SHJC | Shanghai International Airport Co.             |
| 600841 | SHSC | Shanghai Diesel Engine Co.                     |
| 600733 | SQF | Chengdu Qianfeng Electronics Co.               |
| 600100 | TFGF | Tsinghua Tongfang Co.                          |
| 600751 | TJHY | Tianjin Marine Shipping Co.                    |
| 600058 | WKFZ | Minmetals Development Co.                      |
| 600173 | WLDC | Wolong Real Estate Group Co.                   |
| 601168 | XBKY | Western Mining Co.                             |
| 600139 | XBYZ | Sichuan Western Resources Holding Co.          |
| 600657 | XDDC | Cinda Real Estate Co.                          |
| 600638 | XHP | Shanghai New Huang Pu Real Estate Co.          |
| 600755 | XMGM | Xiamen International Trade Group Corp.         |
| 600369 | XNZQ | Southwest Securities Co.                       |
| 601166 | XXYH | Industrial Bank Co.                            |
| 601766 | ZGNC | CSR Corporation                                |
| 600890 | ZFGF | Cred Holding Co.                               |
| 60128 | ZGRS | China Life Insurance Company                   |
| 600028 | ZGSH | China Petroleum & Chemical Corporation         |
Table A1. (Continued.)

| Label | Symbol | Name |
|-------|--------|------|
| 601857 | ZGSY   | PetroChina Company            |
| 601601 | ZGTB   | China Pacific Insurance (group) Co. |
| 601186 | ZGTJ   | China Railway Construction Corporation |
| 601390 | ZGZT   | China Railway Group           |
| 600026 | ZHFZ   | China Shipping Development Company |
| 600036 | ZSYH   | China Merchants Bank Co.      |
| 600030 | ZXZQ   | CITIC Securities Company      |

a Label is the trading ticker of each security on sale in SSE.
b Companies with *ST (Special treatment) in the stock ticker have been in an abnormal financial situation for three consecutive years.

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