Abstract

Listed energy companies play important roles in both energy market and financial market. Relationships between those energy companies also affect both markets. Thus, examining listed energy companies’ relationships is necessary and useful for the further study of the field of energy and finance. To investigate energy companies’ relationships, we applied the Grey Relational Analysis (GRA) and the complex network theory to construct the network. We selected listed energy companies’ ten years’ financial indicators as our input data. We analyzed the network’s evolutionary topological features and explained the implications of these features in detail. We also made panel regression analysis to find out the relationship between network indicators and stock returns. This study provides a new perspective for discovering the relationships of listed energy companies based on financial indicators. It can help government and investors identify the roles of companies in the market so that they can regulate the market in time and make sound investments.

Keywords: Listed Energy Companies; Financial Indicators; Gray Relational Analysis; Complex Networks; Panel Regression Analysis

1. Introduction

Energy companies hold key positions in both the energy and financial markets because energy has not only commercial attributes but also financial attributes [1]. Therefore, energy companies play important roles in the promotion of national and global economies. Currently, to investigate listed energy companies’ relationships, many researchers focus on examining the fluctuation of listed companies’ stock prices [2-5]. Some other scholars study listed companies’ co-ownerships [6-8]. However, data such as stock prices and company ownerships are reflections of the supply and demand of the market and is highly sensitive to the fluctuation of the market. Although financial indicators are less affected by the market, it is helpful to estimate the intrinsic value of stocks. Few scholars use financial indicators derived from financial statements to explore companies’ relationships.

To study the relationships of listed energy companies, we need to calculate the correlation between two companies. In this study, we chose the Grey Relational Analysis (GRA) method to determine listed energy companies’ correlations with others. The GRA method, similar to the Pearson product-moment correlation coefficient (PPMMCC), is commonly applied to measure the similarity between two sets of data. GRA belongs to the grey system theory and can be applied to solve nonlinear problems and measure correlation between series [9]. Under the GRA method, the geometrical similarity between the reference data set and the comparative data set will be calculated. The higher the result is, the more similar the two sets of data are. There are several advantages of GRA. First, unlike Pearson correlation analysis, GRA does not require the normal distribution hypothesis, and data do not need to have a linear relationship. Second, under the GRA method, the calculation is simple and straightforward, and values with different units can be calculated together [10]. Many researchers have already applied the GRA method to measure companies’ correlations of financial performance [11-13]. Due to the features of our data and the advantages of GRA, we chose this method to calculate the correlation.

The complex network theory is a good method for analyzing the features and patterns of a network. A growing number of scholars have applied the complex network theory to their research covering various fields, such as sociology [14-15], biology [16] and economics [17-18]. Many research articles employ the methods to study network topological features [19] and also make evolutionary analysis [20]. Also, some scholars develop the heterogeneous network to reflect relationships more accurately [21]. In terms of the field of energy, scholars have used complex networks to study the price fluctuation of the energy stock market [22] and crude oil trade relationships [23]. Some scholars have already combined GRA to construct a complex network. For instance, a study was conducted to determine the best college coaches by constructing a complex network using the GRA method [24]. Another study used the
GRA method to construct a social network and identify its community structure [25]. In this paper, we combined the GRA method with the complex network theory to construct the network and explore China listed energy companies’ similarities.

We chose ten years’ financial data of listed energy companies in the stock market as our sample and calculated the correlation between those companies based on financial indicators for each year from 2008 to 2017. Then, we construct the undirected weighted network. In the network, we set listed energy companies as nodes and their degree of correlation as their weighted edges. We analyzed the topological features of the network and also its evolutionary features. Then, we did panel regression analysis in order to find out the relationship between network indicators and stock returns. Last but not least, we discussed the result and provided suggestions for the government and investors.

2. Data and Methods

2.1 Data

We downloaded data from the CSMAR Research Database (http://www.gtarsc.com/) on April 10, 2018. We selected ten years’ data from 2008 to 2017. Data were derived from the consolidated annual financial statements of the listed energy companies in the Shenzhen Exchange market and the Shanghai Exchange market. Each set of data covers the listed companies’ names, stock codes, and fifteen financial indicators. Financial indicators can comprehensively reflect a company’s financial position and operation performance. If companies have a high degree of correlations in terms of those financial indicators, it means that they will have similar financial positions and operation performance. Thus, by analyzing companies’ correlation, we can find out their performance similarity.

2.2 Methods

2.2.1 Grey Relational Analysis

We constructed the network based on relationships between listed energy companies. Thus, we took each company as a node (N) and two companies’ correlation as an edge (E). The weight of an edge is the degree of the correlation of two nodes (W). The whole network (G) can be expressed as $G = (N, E, W)$.

To determine $W$, we apply Grey Relational Analysis (GRA) method. GRA includes six steps [26]:

Step 1: construct an initial decision matrix $X = x_i (j)$.

There are $n$ alternatives characterized by $m$ criteria

$$x_i (j) = \begin{bmatrix} x_1 (1) & x_1 (2) \cdots & x_1 (m) \\ x_2 (1) & x_2 (2) \cdots & x_2 (m) \\ \vdots & \vdots & \vdots \\ x_n (1) & x_n (2) \cdots & x_n (m) \end{bmatrix} \quad i=1,2,\ldots,n \quad j=1,2,\ldots,m$$

(1)

where $x_i (j)$ is the value of the $i^{th}$ alternative with respect to the $j^{th}$ criterion.

Step 2: grey relational generating.

For the larger-is-better transformation $x_i (j)$ can be transformed to $x_i^* (j)$ with formula (2):

$$x_i^* = \frac{x_i (j) - \min_{j} x_{ij}}{\max_{j} x_{ij} - \min_{j} x_{ij}}$$

(2)

For the smaller-is-better transformation, the formula to transform $x_i (j)$ to $x_i^* (j)$ is (3):

$$x_i^* = \frac{\max_{j} x_{ij} - x_i (j)}{\max_{j} x_{ij} - \min_{j} x_{ij}}$$

(3)

For the nominal-is-best transformation, $x_i (j)$ can be transformed to $x_i^* (j)$ with formula (4)

$$x_i^* = \frac{1 - \frac{x_i (j) - \min_{j} x_{ij}}{x_i (j) - \max_{j} x_{ij}}}{1 - \frac{x_i (j) - \min_{j} x_{ij}}{\max_{j} x_{ij} - \min_{j} x_{ij}}}$$

(4)

where $x_{id} (j)$ is the ideal value for the $j^{th}$ criterion and is determined by the largest normalized value of each criterion.

$$x_{id} (j) = \max_{i} x_{ij}$$

(5)

Step 3: generate a reference series.

$$x_i^* (j) = \begin{bmatrix} x_i^* (1) & x_i^* (2) & \cdots & x_i^* (m) \\ \vdots & \vdots & \ddots & \vdots \\ x_n^* (1) & x_n^* (2) & \cdots & x_n^* (m) \end{bmatrix}$$

(6)

where $x_i^* (j)$ is the reference value, which is related to the $j^{th}$ criterion and is determined by the largest normalized value of each criterion.

$$x_{id} (j) = \begin{bmatrix} x_1^* (j) & x_2^* (j) & \cdots & x_n^* (j) \end{bmatrix}$$

(7)

Step 4: calculate the difference matrix. In this step, $\Delta_{ij} (j)$ is the differences between the normalized values and their reference values. Next, the difference matrix is constructed as follows:

$$\Delta_{ij} (j) = \begin{bmatrix} \Delta_{1j} (1) & \Delta_{1j} (2) & \cdots & \Delta_{1j} (m) \\ \Delta_{2j} (1) & \Delta_{2j} (2) & \cdots & \Delta_{2j} (m) \\ \vdots & \vdots & \ddots & \vdots \\ \Delta_{nj} (1) & \Delta_{nj} (2) & \cdots & \Delta_{nj} (m) \end{bmatrix}$$

(8)

Step 5: calculate the Grey correlation coefficient. The Grey relational coefficient is calculated by formula (9)

$$\gamma_{ij}(j) = \frac{\min_{m} \sum_{j=1}^{m} \Delta_{ij}(j)}{\max_{m} \sum_{j=1}^{m} \Delta_{ij}(j)}$$

(9)

where $\xi (0 \leq \xi \leq 1)$ is the distinguishing coefficient.

Step 6: calculate the Grey relational grade. If all decision criteria have an equal importance degree, the grey relational grade $\Gamma_{ij}$ can be calculated as follows:

$$\Gamma_{ij} = \frac{1}{N} \sum_{j=1}^{n} \gamma_{ij}(j)$$

(10)

where $\gamma (j)$ values represent the relative importance weights of the criteria. $\Gamma_{ij}$ is the grey relational grade and indicates the magnitude of similarity measured between the alternative series and reference series.

2.2.2 Topological Features Calculation

(1) The degree of a node represents the number of
nodes being connected. Different with the degree, the weighted degree considers the weight of edges. If the weight between two nodes is higher, the weighted degree will be larger.

\[ S_v = \sum_{w_{ij} \in E} w_{ij} \]  

where \( S_v \) is the weighted degree of node \( v \); \( N \) is the set of neighbor nodes \( v \); \( w_{ij} \) is the weight of the edge connecting node \( v \) and \( v_j \).

2) Clustering coefficient represents the connectivity of the neighbor nodes of a given node,

\[ C_i = \frac{E_i}{\binom{2k_i}{2}} \]  

where \( C_i \) is the clustering coefficient of node \( i \), and \( E_i \) is the actual number of edges around node \( i \). \( R_i \) is a neighbor of node \( i \) and \( \binom{2k_i}{2} \) represents its potential number of ties of \( R_i \).

3) Closeness centrality reflects the location of nodes in the network. If a node has a high value of closeness centrality, it will have a short path reaching other nodes. It also indicates that the node locates in the center of the network. The closeness centrality is calculated as follow:

\[ CC_i = \frac{1}{\sum_{j \neq i} d_{ij}} \]  

where \( CC_i \) is the closeness centrality of node \( i \), \( N \) is total number of nodes in the network, and \( d_{ij} \) is the distance from node \( i \) to node \( j \).

4) Betweenness centrality refers to the number of shortest paths that a node being passed through. If a node has a high betweenness centrality, it will act as an intermediary and control the information transmission [27]. The betweenness centrality is calculated by the following equation:  

\[ B_{i,e} = \sum \sum \frac{f_{ij}}{f_{ij}(e)} \]  

Where \( B_{i,e} \) is the betweenness centrality of node \( e \), \( N \) is the total number of nodes, \( f_{ij} \) is the number of shortest paths between \( i \) and \( j \), and \( f_{ij}(e) \) is the number of the shortest paths between \( i \) and \( j \) through \( e \).

2.2.3 Panel Regression Model

We applied annual stock returns of energy listed companies as our input data. The stock returns are calculated according to the following formula in (16):

\[ R = \ln P_{end} - \ln P_{begin} \]  

Then we constructed the panel regression model. The formula for the regression model is shown below:

\[ y_t = b_0 + b_1 x_{1,t} + b_2 x_{2,t} + \ldots + b_k x_{k,t} + u_t \]  

where \( y_t \) represents the dependent variable and the stock returns of the energy listed company, \( x_{k,t} \) is the independent variable at time \( t \), and \( b_k \) is the coefficient of independent variable.

We set stock returns (sr) as the dependent variable. Company’s net assets (na) and net profits (np) can influence stock returns. Thus, we set them as control variables. We set weighted degree (wd), clustering coefficient (cc), closeness centrality (ct), and betweenness centrality (bc) as independent variables. We also proposed four hypotheses. Hypothesis 1: The larger the value of the weighted degree of a company, the higher the stock return is. Hypothesis 2: The larger the value of the clustering coefficient of a company, the higher the stock return is. Hypothesis 3: The larger the value for the betweenness centrality of a company, the higher its stock return is. Hypothesis 4: The larger the value for the closeness centrality of a company, the higher the stock return is.

3. Calculation and Analysis

3.1. Overview of the network

Figure 1 shows the visibility of network in 2008 and 2017. We set 0.85 as the threshold and filtered out edges whose value were below 0.85 so that the network structure can be presented more clearly. The network is composed by several communities, which are in different color. Some are connected closely and some are isolated. The overall structure remained stable.
3.2 Indicators analysis

A node with a large weighted degree means that it has good connection diversity. In the paper, a company with a larger weighted degree means its financial position and operating performance are similar to more listed energy companies. Table 1 shows the top 10 companies with the highest weighted degree from 2008 to 2017. SH.600167 appears five times, and SH.600900 and SH.002700 appear four times. SH.600900 belongs to gas production and supply industry and SH.002700 belongs to gas production and supply industry. Besides, as time went by, more natural gas production and supply companies and hydro power production and supply companies appeared in the rank.

The clustering coefficient also can measure the connection degree of a listed energy company’s neighbor companies. If a listed energy company has a higher clustering coefficient, more of its neighbors are "intermediary". We find that a company with high value of betweenness centrality does not have a very high value of closeness centrality. It indicates that intermediary companies are not quickly influenced by the changes of the market. We listed top ten companies with highest betweenness centrality in Table 2. SH.600116 appeared six times, SH.600505 appeared five times and SH.002267 appeared four times. Both SH.600116 and SH. 600505 belong to electricity and heat production and supply industry. SH.002267, which was not shown in the rank until 2012, belongs to natural gas production and supply industry.

3.3 The relationship between company similarity and stock returns

In order to find out the impact of the degree of company performance similarity on stock returns, we shown in figure 3. The clustering coefficient changed slightly. It increased from 2008 to 2011 and fluctuated during the next four years. It started to increase since 2016. Closeness centrality reflects the ability of nodes to influence other nodes. If a company has a higher closeness centrality value, the company will more quickly get affected by the changes of the market. Figure 4 shows the relationships between weighted degree and closeness centrality for the network in 2008 and 2017. It also reflects the change of the value of average closeness centrality for the decade. The average value of closeness centrality increased slightly from 2008 to 2017. The other finding is that the closeness centrality has a positive relationship with the value of weighted degree.

Table 1. Weighted degree ranking from 2008 to 2017

<table>
<thead>
<tr>
<th>Rank</th>
<th>Year</th>
<th>2008</th>
<th>2009</th>
<th>2010</th>
<th>2011</th>
<th>2012</th>
<th>2013</th>
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Table 2. Betweenness centrality ranking from 2008 to 2017

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constructed a panel regression model. To maintain consistency, we only selected companies listed in the stock market every year from 2008 to 2017. First of all, we did unit root test, and found that unit roots did not exist. Then we conducted cointegration test and the result showed that the data was stationary. We also did residual test and the result indicated autocorrelation and cross-sectional dependence existed. As a result, we applied generalized linear regression model to do the regression. The results are shown in Table 3.

From Table 3, we find that all network indicators have significant influence on stock returns. Weighted average has a negative relationship with stock returns. Clustering coefficient has a positive relationship with stock returns. The closeness centrality has a positive relationship with stock returns and it has more remarkable impact on the returns. The betweenness centrality has a positive relationship with stock returns as well.

| sr | Coef. | Std. Err. | z | P>|z| |
|-----|-------|-----------|---|-------|
| wd  | .0981036 | .00347198 | -2.77 | 0.068 | -1.9753251 | .028682 |
| cc  | .0000268 | .0415764 | 1.25 | 0.210 | -.294255 | .133511 |
| bc  | .0159147 | .0165858 | 0.96 | 0.337 | -.1656929 | .0494224 |
| ct  | .2803055 | .2302196 | 1.23 | 0.219 | -.1682167 | .734227 |
| na  | -.09595955 | .0057504 | -1.66 | 0.096 | -.09208031 | .017111 |
| np  | -.0056902 | .0016372 | 3.47 | 0.001 | .00024773 | .0088956 |
| cons | .4644747 | .1945653 | 2.52 | 0.012 | .102751 | .8261985 |

Table 3. Result of Panel Regression Analysis

4. Discussion and Conclusion

First, we analyzed the network as a whole. The structure of the network did not have significant change over ten years. Although the number of companies increased, companies became less similar from 2012 to 2014. The reason is that in 2012, the global energy market showed poor performance. Price of energy products, especially coal products, fell sharply. The overall performance of China listed energy companies were affected with various degrees. Also, as companies applied different measures to control the risks, the correlation between them decreased. As a result, the number of edges decreased for those two years. The results above indicate that companies’ financial position, operating performance are not only influenced by broad environment, but also related to companies’ sensitivity to the changes of the market. When China’s energy market is in a depression, government and investors should pay more attention to individual company to see their reactions in order to issue proper policies and change investment strategies.

Secondly, we ranked top ten companies with highest weighted degree. In order to study listed energy companies and China’s energy market, people can do more detailed research on those companies showed in the rank as they are representatives. Also, as time passed by, more hydro power companies and natural gas companies appeared in the rank. Companies whose main business related to hydro power and natural gas power made rapid progress in recent years. Their financial position and operation performance became much better and gradually reach to the similar level of traditional energy companies. The trend of China energy development explained the phenomenon that more hydro power companies and natural gas companies appeared in the top ten rank. Not only policy makers, but also investors should focus more on hydro power industries and natural gas industries.

Thirdly, we calculated the clustering coefficient of the network. The value did not have significant change from 2008 to 2017. It increased slightly during first four years, fluctuated for the next four years and began to increase again since 2016. The increasing clustering coefficient means that the network is getting more ordered. The fluctuation was also largely due to the global economic environment, politics, and other factors. Since 2011, the wars and the political instability brought by oil producing countries, the global economic downturn and the sustained low-speed growth of energy consumption led to the structure fluctuation of energy networks. Correspondingly, the network growth in 2008-2011 and 2016-2017 was due to the increased energy demand in emerging economies, particularly the expansion of natural gas. At the same time, the result indicates that although China energy market was influenced by many factors, it is gradually becoming an ordered market.

Fourthly, we analyzed closeness centrality and betweenness centrality. We find that the closeness centrality has a positive relationship with the value of weighted degree. It indicates that if the company is more similar with other companies, it will be more quickly influenced by factors that could affect the whole market and more dependent on other companies’ behavior. In terms of betweenness centrality, the company will become an intermediary if it has a high value of betweenness centrality. It will spread information among the energy market. A company, which has a high value of betweenness centrality, does not has a very high value of closeness centrality. Thus, companies that act as intermediaries are not quickly affected the changes and more independent. The rank reflects that natural gas companies gradually taking the role of mediation as the development of natural gas. In sum, as energy market in China is greatly influenced by global energy market, global economy and government policies, it is necessary for the market participants to remain vigilant and monitor the changes.

Last but not least, we found that network indicators have significant impact on stock returns. Weighted average has a negative relationship with stock returns. In the market, companies which have more similar companies have less stock returns. Other indicators have positive relationships with stock returns. In other words, companies which take important roles of gathering together similar companies have higher stock
returns. Besides, intermediary companies and companies being affected by changes more quickly also have higher stock returns. Based on the result, in order to have higher stock returns, investors can analyze companies position in the network and invest in energy companies which have lower weighted degree, higher clustering coefficient, higher closeness centrality and higher betweenness centrality. The analysis provides a useful way for investors to make wise decision.

Reference


