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Complex networks analysis in Iran stock market: The application of centrality

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HIGHLIGHTS

- Iran's stock market network has been created based on the threshold method.
- Centrality is calculated based on four criteria: Degree centrality, betweenness centrality, closeness centrality and eigenvector centrality.
- Stocks with a higher market capitalization, greater fluctuations, higher transaction volume and higher liquidity are more central.
- An industry's more central position in the network attests to its higher relative growth.

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ABSTRACT

A big data set can often be illustrated by the nodes and edges of a big network. A large volume of data is generally produced by the stock market, and complex networks can be used to reflect the stock market behavior. The correlation of stock prices can be examined by analyzing the stock market based on complex networks. This paper uses the stock data of Tehran Stock Exchange from March 21, 2014, to March 21, 2017, to construct its stock correlation network using the threshold method. With an emphasis on centrality in complex networks, this article addresses key economic and financial implications that can be derived from stock market centrality. Central industries and stocks are thus identified. The results of the analysis of stock centrality suggest that stocks with a higher market capitalization, a greater risk, a higher volume of transactions and a lower debt ratio (i.e. greater liquidity) are more central. These stocks attract more customers due to their attractive investment features and thus have a greater market influence. The review of the relationship between centrality and the growth of industries shows that an industry or a sector with greater economic growth has a higher centrality value and is positioned more centrally in the stock market network.

1. Introduction

One of the most important problems in modern finance is finding efficient methods for visualizing and summarizing stock market data. A significant volume of daily data is produced by the stock market, and this information is presented by thousands of plots and separately represents the price movement of each stock. When the number of stocks increases,

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these plots become more complicated to analyze [1]. Moreover, if there are multiple heterogeneous components, the stock market behavior becomes complex [2]. In addition, stock price fluctuations are not independent of each other and have a strong correlation with the business and industries to which the stock belong [3]. Based on recent investigations, the complex network method is highly recommended for visualizing and summarizing stock data and studying the correlation of stock prices [4,5].

A crystal clear image of the inner structure of the stock market can be presented by complex network analysis [2]. In this method, unlike classic cost–benefit methods, stock price variations are affected by group behaviors. Studying the structure of the stock market network helps explain the stock market behavior and the interaction among its factors. This method therefore challenges the independent variable assumption of the current linear analysis methods that are based on identifying the effects of several independent variables on a dependent variable [6].

The stock market network is constructed based on the correlation between stock price returns. Studying the correlation matrix has a long history in financial affairs and is the main foundation of Markowitz theory about securities market [7]. The correlation analysis of financial markets is an important issue for market policymakers and activists, such as portfolio managers, and is also crucial for risk management and asset allocation [8]. Various studies conducted to analyze complex networks in the stock market also confirm these findings. Brida et al. [9], Zhong et al. [10] and Zhao et al. [11] analyzed the topologic structure of the financial market network and proposed network analysis as a helpful guide for investors. Eberhard et al. [12] investigated the network properties of the stock market in Chile. Their results showed that the structure of the stock market network in Chile can affect the stocks' transaction volume and return in the market. Sharma et al. [13] constructed the stock market network for India based on the correlation among market stocks using the threshold method and concluded that the network analysis of the Indian stock market can provide a better understanding of stock correlations in this market.

As one of the network criteria, centrality has a major role in identifying the internal structure of a stock market network. Extensive theoretical research has been carried out on centrality in networks; examples include studies by Bonacich [14], Bonacich and Lloyd [15], and Grassi et al. [16–20]. Many empirical studies conducted on stock market centrality have used centrality to identify important stocks [21–24]. After identifying the topological structure of the stock market network of 100 companies in Italy, Coletti [25] found that the most important companies are petrochemical, natural gas and insurance companies, which are positioned centrally in the stock market network and have great significance. In a study by Majapa and Gossel [26] on the market structure in South Africa, the most linked and connected stocks were in the financial and resource sectors.

Although the application of networks has been studied in various economic and financial fields, such as job markets [27,28], the diffusion of technology [29–33], ownership relationships between companies and shareholders' networks [34–40], formal and informal organizations [41–46], R&D collaborations [47–50], consumer preferences [51], the interbank and credit market [52–54], the stock market network [40,55,56], e-trade [57] and the world trade web [58,59], very few studies have addressed the economic and financial implications of centrality in economic and financial networks. Corrado and Zollo [60] created a network based on ownership relationships among Italian companies and calculated the betweenness centrality to show that although privatization alters ownership relationships, the role of key players remains fairly stable. D'Errico et al. [61] calculated the betweenness centrality in the Italian shareholding network and found that the more central companies act as a reservoir and absorb the external shocks. In another study, Spelta and Araújo [62] calculated the closeness centrality in the international interbank network to form a chain of countries reflecting the sequence of the occurrence of financial crises. According to their study, countries with a constantly-increasing closeness centrality are those in which there is an opportunity for debt transfer as a result of low taxation policies. Kazemilari and Djauhari [63] calculated the centrality criteria in the stock market network and found that the changing position of centrality in a stock market network has economic origins, as a company's economic performance can affect its stocks' hub position.

The present article thus addresses important economic and financial implications that can be extracted from centrality in the stock market by constructing the stock market network of Iran (which has less been analyzed due to its small size and the lack of reliable historical data) and calculating the centrality criteria. For the greater rigor of the study findings, four centrality criteria are considered, and the network's central stocks are identified based on these four criteria (degree, betweenness, closeness and eigenvector centralities). Then, to extract the financial implications of centrality in the stock market, the Sharpe ratio distribution is obtained for the low, middle and high terciles of stock centrality. The significantly higher mean Sharpe ratio as ascending from the bottom tercile to the middle and high tercile of the centrality distribution indicates that, on average, higher Sharpe ratios are observed in stocks with a higher centrality. Consequently, given the definition of the Sharpe ratio, it is necessary to investigate the relationship between stock centrality and risk. The results of the Sharpe ratio and the positive and significant correlation between β-CAPM and the stock centrality suggest that stocks with a higher centrality have higher risks and a more favorable risk-adjusted performance. Cross-sectional regression is then estimated to identify the financial variables determining the stock centrality. The regression results imply that companies with a larger size, higher market capitalization, higher volume of transactions and lower debt ratios (i.e. greater liquidity) are more central, which means that these stocks attract more customers and thus have greater market influence due to their attractive investment features. As for the economic implications of these results, it can be argued that, since central stocks are connected to a larger number of stocks, they are also exposed to aggregate risks and shocks in addition to their specific individual risks. Central stocks can therefore reflect the incidence of an economic phenomenon or shock. The status of an industry is therefore expected to be explained by the centrality of its stocks. For a more accurate assessment of this issue, the centrality of each industry has been calculated by averaging the centrality values of its stocks, and their relationship with the value-added of that industry (which implies the industry's growth) has also been assessed. The results suggest that industries with a greater value-added coefficient or growth are in a more central position in the network. The results on the centrality of the main economic sectors also confirm this finding. In other words, an industry or sector with a greater economic growth will have a higher centrality value, and consequently, will be positioned more centrally in the stock market network. The rest of this article explains the analytical method used and then presents the results and makes a conclusion.

2. Methodology

2.1. Constructing the stock market's correlation network

The complex networks theory is derived from graph theory and was developed several decades ago as a theoretic outline to understand networks' structural characteristics [64]. A network is defined by the trinal $G = (V, E, f)$, where V is a finite set of nodes, $E \subseteq V \otimes V = \{e_1, e_2, \ldots, e_m\}$ is a set of connections or edges, and f is a map that connects some components in E to a pair of V, so that if $v_i \in V$ and $v_j \in V$, then $f : e_p \longrightarrow [v_i, v_j]$ and $f : e_q \longrightarrow [v_j, v_i]$. A simple network without multiple links and recursive rings is defined by the binary $G = (V, E)$, where V is a finite set of nodes and E is a symmetric and non-reflexive relation on V.

To construct the stock market network, $p_i(t)$ is taken as the closing price of stock i on day t. The stocks' return on day t is then defined as follows:

$$r_i(t) = lnp_i(t) - \ln p_i(t-1) \tag{1}$$

The correlation between two stocks is considered a component of correlation matrix C, which is obtained by the following formula:

$$c_{ij} = \frac{\langle r_i r_j \rangle - \langle r_i \rangle \langle r_j \rangle}{\sqrt{\left(\langle r_i^2 \rangle - \langle r_i \rangle^2\right)\left(\langle r_j^2 \rangle - \langle r_j \rangle^2\right)}} \tag{2}$$

where r is the return and the bracket shows the mean time during the period. c_{ij} can vary between -1 and 1. $c_{ij} = 1(-1)$ means that firms i and j are totally correlated (anti-correlated), while $c_{ij} = 0$ means they are uncorrelated.

The stock market network is constructed using the threshold method, which is well known in financial networks [3,65–68], to reduce the complexity and facilitate the analysis and retain the most significant relationships. The main idea of constructing a stock network is therefore proposed as follows:

Assume a set of stocks that are illustrated by network nodes. A specific threshold of θ, $0 \le \theta \le 1$, is also determined and a no-direction edge is plotted between nodes i and j if the absolute value of c_{ij} is equal to or greater than θ. Different θ values clearly define networks with the same sets of vertices and different sets of edges. The threshold method therefore includes only the correlations among stocks exceeding a specific θ value. The advantages of the threshold method compared to other reduction techniques such as minimal spanning tree and planer graphs include avoiding the loss of any necessary data in the network constructed, whereas both methods cited are likely to eliminate highly-correlated edges [3]. The threshold value of θ is determined based on the methodology proposed by Xu et al. [69]. Since any changes in the constructed network have to be consistent with changes in the actual market, Xu et al. [69] proposed a consistent function between the two and chose the optimal threshold with a maximized consistency. The correlation matrix C_i and the network N_i are thus constructed for each value of $\theta_i \in [0, 1]$ and the below function is then measured:

$$G_{\theta_i} = \frac{\langle D_C D_N \rangle - \langle D_C \rangle \langle D_N \rangle}{\sigma_{D_C} \sigma_{D_N}} \tag{3}$$

This function measures the consistency between the changes in the correlation matrix and network, in which D_C and D_N

are changes in the matrix and changes in the network, and σ_{D_C} and σ_{D_N} are their standard deviations, and the optimal threshold value is chosen according to the numerical method that follows:

$$\hat{\theta} = arg \max_{\theta_i} \left\{ G_{\theta_i} \right\} \tag{4}$$

Based on Zhang et al. [70], this paper takes all the negative and positive correlations whose absolute values are greater than the threshold value, and the absolute value of the correlation is then used to weight the edges of the network. $G = (V, E, W)$ represents a stock network where V is the set of vertices, E is the edges and W is defined as follows:

$$W = \begin{cases} w_{ij} = \left| c_{ij} \right|, & i \neq j \ and \left| c_{ij} \right| \geq \theta \\ w_{ij} = 0, & else. \end{cases} \tag{5}$$

If $w_{ij} \neq 0$, there is one edge between nodes i and j.

2.2. Centrality

Centrality describes the position of points in a network [71]. Centrality is a broad concept applied for identifying and determining the most important actors or the most important interactions in a network; it can also be used to determine the main nodes in a network and identify the most connected stocks in the market. This study examines network nodes' centrality using four centrality criteria, including degree centrality, betweenness centrality, closeness centrality and eigenvector centrality.

2.3. Degree centrality

The degree centrality of a node in a network is the number of links that node has with other nodes in that network [72]. Degree centrality is the number of direct links between a given actor and other actors in the network. A high degree centrality is inferred when an actor has many links in a network, and a broad relationship thus exists between this actor and the others. Due to these broad relationships, resources are more reachable for this actor and it is therefore regarded as a more central actor. This benchmark is defined by the number of direct links in an operator. The degree centrality of node k is defined as follows:

$$C_D\left(k\right) = \sum_{i=1}^{n} \alpha(i, k) \tag{6}$$

where n is the number of existing nodes in the network and $\alpha(i, k)$ is equal to 1 if the two nodes are connected to each other, and 0, otherwise. To explain the weighted networks, degree centrality is generally defined by the sum of the weights and is formulized as follows [73]:

$$C_D^W\left(k\right) = \sum_{i}^{N} w_{ki} \tag{7}$$

where W is the weighted adjacency matrix and w_{ki} the weight of the relationship between k and i.

2.4. Betweenness centrality

The betweenness centrality index of a node is the number of times that the node is in the shortest path between each pair of nodes in a network. The nodes with a high betweenness centrality have an important role in network connection and also in information circulation in the network [74]. A node with a high betweenness centrality is like a bridge that connects different parts of a network, and when eliminated from the network, all the relationships will be affected in the network [75]. Betweenness centrality implies the amount of intermediation in a network. Betweenness centrality index is calculated as follows for node k:

$$C_B\left(k\right) = \sum_{i=1}^{n} \frac{g_{ij}(k)}{g_{ij}}, i \neq j \neq k \tag{8}$$

where g_{ij} is the shortest path connecting the two nodes i and j and $g_{ij}(k)$ the shortest path connecting the two nodes that also passes through node k, based on the sum of the weights.

Table 1
Stock ranking based on degree, betweenness, closeness and eigenvector centrality criteria.

Rank	Degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality
1	Shargh Cement	Sabet Khorasan	Shargh Cement	Shargh Cement
2	Sepahan Cement	Shahroud Sugar	Mobarakeh Steel	Saman Gostar
3	Mobarakeh Steel	Sina Chemical	Saman Gostar	Sepahan Cement
4	Kermanshah Petr.	Sahand Rubber	Pars Tousheh	Spahan Naft
5	Spahan Naft	Iran Zinc Mines	Iran Carbon	F. & Kh. Cement
6	Mobin Petr.	Mobarakeh Steel	Mobin Petr.	Mobarakeh Steel
7	Iran Carbon	Tuka Trans.	Metals & Min.	Behbahan Cement
8	F. & Kh. Cement	Inf. Services	Spahan Naft	Pars Khazar
9	Saman Gostar	Offset	Sepahan Cement	Mobin Petr.
10	Pars Tousheh	Metals & Min.	Behbahan Cement	Kermanshah Petr.

2.5. Closeness centrality

The closeness centrality index of a node is the mean of the length of the shortest paths between the node and all other nodes in the network. The nodes with a higher closeness centrality index in the network are therefore more powerful and play a more central role in it. In addition, these nodes are more accessible for the other nodes. The closeness centrality index for node k is defined by the following formula:

$$C_C(k) = \sum_{i=1}^{n} d(i,k)^{-1} \tag{9}$$

where $d(i,k)$ is the shortest path between the two nodes i and k based on the sum of the weights.

2.6. Eigenvector centrality

Just like degree centrality, eigenvector centrality is dependent on its neighbors, except that it is not dependent on the number of its neighbors, but on their degree of importance. A node with a smaller number of more important neighbors has a higher eigenvector centrality compared to a node with more neighbors of less importance. This measure is closely related to Katz centrality, and if A is the weighted adjacency matrix and λ the constant, the eigenvector centrality index of node k is obtained by the following equation:

$$C_E(k) = \frac{1}{\lambda} \sum_{i=1}^{n} A_{ik} C_E(i) \tag{10}$$

And its matrix form is displayed as follows:

$$AC_E = \lambda C_E \tag{11}$$

which means C_E is an eigenvector of the A matrix.

3. Results

3.1. Calculation of centrality in the stock market network

During the years from March 21, 2014 to March 21, 2017, a number of stocks that were illiquid in the Iranian stock market or had been suspended over a great length of time during the study period were excluded from the study data. Therefore, after preprocessing the data, only 246 out of more than 360 stocks traded on Tehran Stock Exchange were deemed suitable for this research. The return of each stock is thus calculated based on its daily closing price and the correlation between the stock returns was calculated, and based on this correlation, relationships were formed between the stocks and the stock market network was constructed. The optimal threshold value is selected based on the methodology proposed by Xu et al. [69] and successive selections of θ are thus tested. By choosing $\theta_0 = 0$ and $\Delta\theta = 0.1$, a sequence of discrete threshold values is created, and the relevant network is constructed for each threshold value θ_i and the consistency function G_{θ_i} is calculated. Accordingly, $\theta = 0.4$ has been selected as the optimal threshold value out of successive discrete selections of θ_i since it maximizes G_{θ_i}. Table 1 presents the central stocks of the stock market network based on degree, betweenness, closeness and eigenvector centrality.

According to Table 1, Shargh Cement Co. ranks first in centrality based on its degree, closeness and eigenvector centrality, but is replaced in this position by Sabet Khorasan Co. based on the betweenness centrality criterion. With the highest degree centrality score, Shargh Cement Co. has the greatest influence over the other stocks, and with the highest closeness centrality, it has the greatest speed of data spreading to other stocks; in addition, having the highest

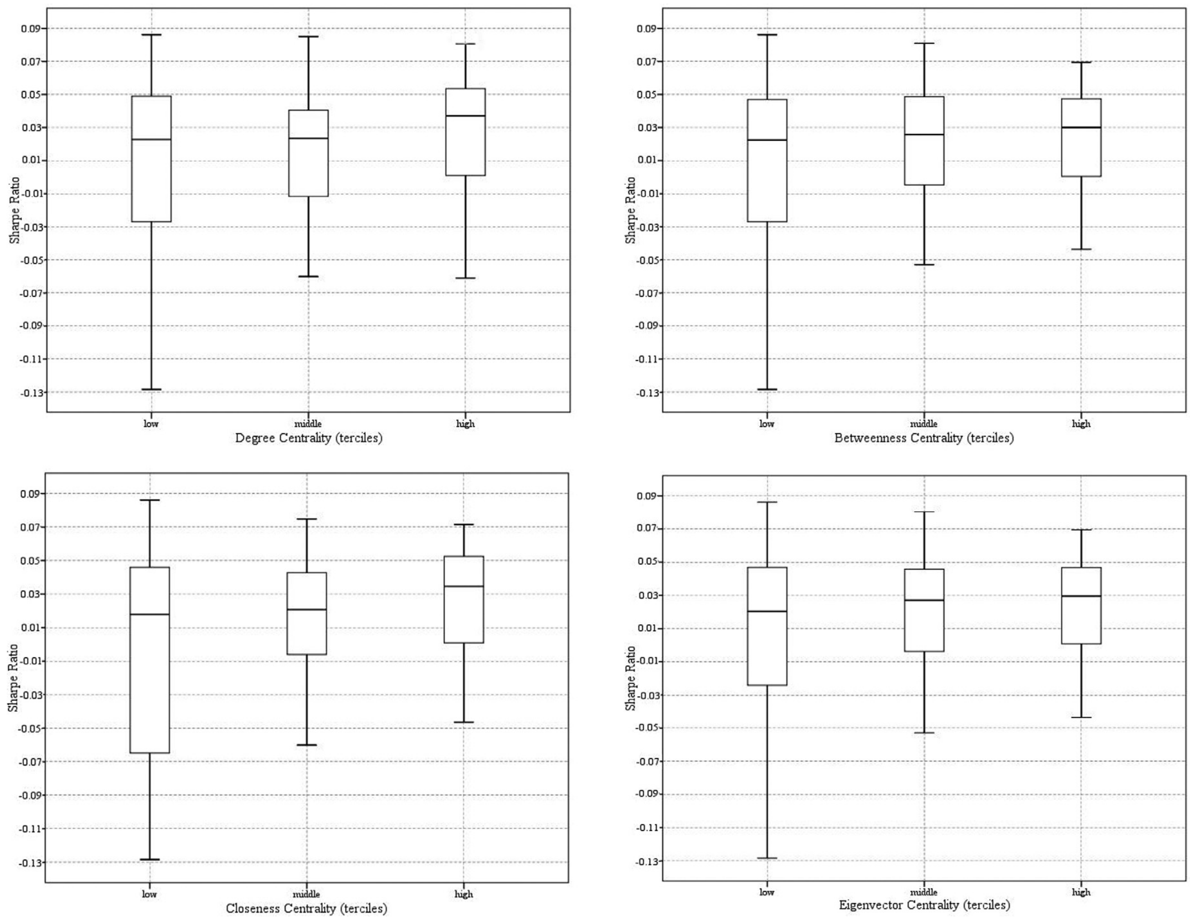

Fig. 1. Sharpe ratio distribution for the low, middle and high terciles of stock centrality.

Table 2
The comparison of the mean Sharpe ratio for the low, middle and high terciles of stock centrality.

Terciles	Degree centrality		Betweenness centrality		Closeness centrality		Eigenvector centrality	
	Mean	F-stat (P-value)	Mean	F-stat (P-value)	Mean	F-stat (P-value)	Mean	F-stat (P-value)
Low	0.011		0.018		0.011		0.014	
Middle	0.025	3.01	0.024	3.45	0.021	3.02	0.023	3.22
High	0.031	(0.04)	0.028	(0.03)	0.031	(0.04)	0.026	(0.04)

eigenvector centrality gives it the greatest power due to adjacency to important stocks. With the greatest betweenness centrality, Sabet Khorasan Co. controls the flow of information among stocks. Based on the calculated centrality criteria, the stocks of Mobarakeh Steel Co. (based on all four criteria) and Sepahan Cement Co., Spahan Naft Co., Mobin Petr. Co. and Saman Gostar Co. (based on degree, closeness and eigenvector centrality) are among the top ten central stocks.

3.2. Fundamental guidelines for stock centrality

Considering the fundamental role of centrality in this study, this section presents fundamental guidelines derived from the stock market network of Iran. If the stocks are classified in ascending order into three terciles, i.e. low, middle and high terciles, calculating the Sharpe ratio for each of the stock in these three terciles shows that the dispersion of risk-adjusted returns' distribution is not constant in the network. Fig. 1 and Table 2 show the box plot of the Sharpe ratio and the mean comparison test for the high, middle and low terciles of stock centrality.

According to Table 2 and Fig. 1, besides the significant differences in the mean Sharpe ratio between these three categories, the Sharpe ratio distribution shrinks in stock categories with a higher centrality. In addition, as shown in

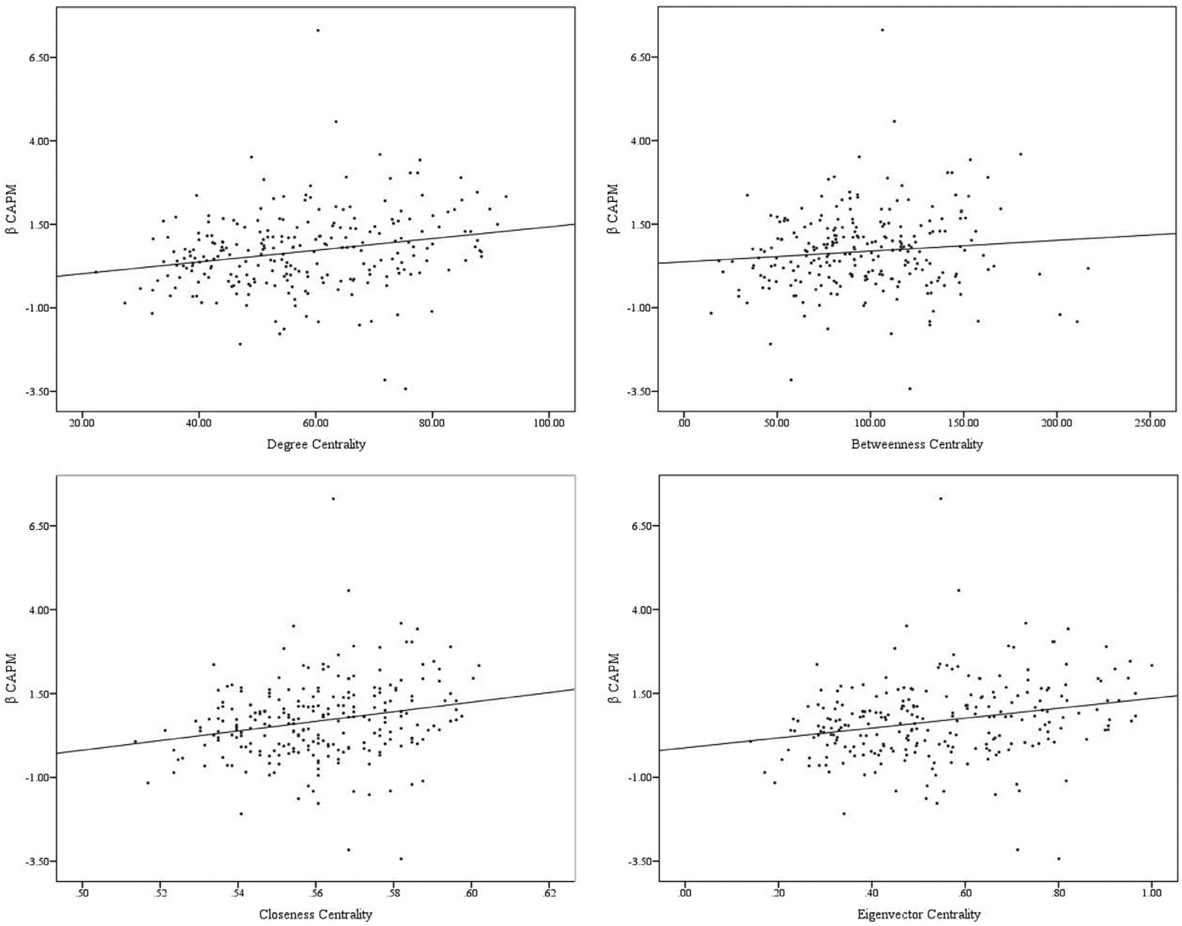

Fig. 2. The relationship between the stock centrality criteria and β-CAPM.

Table 3
Linear regression coefficients of stock centrality criteria and β-CAPM.

	Degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality
Coefficients	0.02	0.01	14.31	1.47
	[3.61]	[2.25]	[3.55]	[3.90]
	(0.00)	(0.03)	(0.00)	(0.00)

The numbers in brackets indicate the t-stat and the numbers in parenthesis indicate the significance level.

Table 2, the mean Sharpe ratio increases significantly in stock categories with a higher centrality. Given the significant increase in the mean Sharpe ratio as ascending from the low tercile to the middle and high tercile of centrality distribution, the expectation is to have higher Sharpe ratios among the higher-centrality stocks on average. Since the Sharpe ratio assesses the risk-adjusted return by definition, the relationship between stock centrality and risk is assessed in the next step. The β-CAPM is also calculated for each stock and scatter plots are presented in Fig. 2 to examine the relationship between β-CAPM and the stock centrality criteria.

The scatter plots of stock centrality and β-CAPM show an increasing relationship between β-CAPM and the stock centrality criteria. In addition, as shown in Table 7, the correlation between these two variables is accepted by Pearson's correlation test, and the significance of the positive coefficients of regression lines is approved as shown in Table 3. This table shows that the more central stocks are bonds that are likely to bear a higher amount of systematic risk. It is thus expected that the bonds with a higher centrality bear a higher risk and have a better risk-adjusted performance.

To identify the key financial stimulants of stock centrality, the following cross-sectional regression is estimated:

$$Cntr_i = \beta_0 + \beta_1 ROA_i + \beta_2 Lev_i + \beta_3 Vl_i + \beta_4 MC_i + \beta_5 Vlat_i + \epsilon_i \tag{12}$$

Table 4
The results of the cross-sectional regression estimation.

	Model 1	Model 2	Model 3	Model 4
ROA	−0.34 (0.61)	−0.57 (0.56)	−0.001 (0.32)	−0.004 (0.19)
Lev	−14.80* (0.03)	−19.74* (0.03)	−0.01* (0.04)	−0.19* (0.02)
Vl	15.35* (0.02)	43.45* (0.04)	0.02* (0.01)	0.11* (0.00)
MC	93.20* (0.03)	153.43* (0.01)	0.09* (0.00)	1.11* (0.01)
Vlat	0.27* (0.01)	0.02* (0.04)	0.001* (0.03)	0.003* (0.03)

Independent variable for models 1, 2, 3 and 4 is degree centrality, betweenness centrality, closeness centrality and eigenvector centrality respectively. P-values are reported in parentheses.
*Significance level at 5%.

where $Cntr_i$ is the centrality of stock i and a dependent variable, and the independent variables include ROA_i as the mean return on assets ratio at the year-end for i company, Lev_i is the company's mean ratio of debt to total assets at the year-end, Vl_i is the logarithm of its mean volume of transactions over each year, MC_i is the logarithm of the mean market capitalization at the year-end and $Vlat_i$ is the mean fluctuation in stock i over the year. Table 4 presents the results of the cross-sectional regression estimation based on the four centrality criteria using the OLS method. The F-stat is significant in all the regression models (P-value = 0.00) and the models are therefore deemed valid.

Based on the results of the coefficient estimation with centrality as the dependent variable, *ROA* is not significant. The coefficients are negative for *Lev* and positive for *MC*, *Volume* and *Vlat*. The most central stocks are therefore those that have a lower debt ratio and higher market capitalization and transaction volume and fluctuation.

The results presented in Table 4 suggest that companies with a larger size and a higher market capitalization are more central, which means that the market's larger stocks have a great influence in the market. Large cap stocks have a larger number of customers, and their behavior often dictates the total market index. Consequently, when the total index is positive, investors become attracted to buying the stock of large companies. Moreover, stocks with a high volume of transactions will be more central and have a great market influence due to their larger number of customers. According to the results, highly fluctuating stocks are more central, and the more central stocks are also exposed to more shocks since they are linked to more stocks and therefore pose more risk. Marginal stocks, however, are less linked to other stocks and are therefore exposed to less shocks and have less fluctuations and less risk. Stocks with lower debt ratios are more central because of their higher liquidity and will have a larger number of customers and a greater market influence as a result.

The results of examining the relationship of centrality with β-CAPM and the Sharpe ratio and also the cross-sectional regression estimation can have important economic implications. Central stocks are at a greater risk of shocks due to being linked to more stocks. Shocks can directly hit a particular group of stocks, but the central stocks will necessarily be exposed indirectly to these shocks. More centrally-positioned and larger cap stocks with a higher transaction volume will therefore be at a greater risk. Therefore, in addition to their particular individual risks, central stocks are also exposed to aggregate risks and shocks. As a result, central stocks can reflect an economic phenomenon or shock. It is therefore expected that the assessment of the centrality of stocks belonging to an industry describe the status of that industry. This issue will be further assessed by considering centrality in industries.

3.3. Centrality in industries

A general review of industries and the network led to the finding that the network stocks are mainly divided into four economic sectors based on their activity, including services, manufacturing and mining, agriculture and oil. With a more detailed classification, the network stocks can be divided based on big industrial plants of Iran (the International Standard of Industrial Classification — ISIC). The centrality of each industry or sector is thus obtained by calculating the mean centrality of the stocks belonging to it.

Table 5 has listed Iran's big industrial plants based on the centrality criteria. This table also presents the value-added coefficient of each plant in the production index of the big industrial plants of Iran in a column. The value-added method offers one way for calculating GDP or the economic growth index, and is the sum of the added values of different economic sectors. The value-added of each industry or sector is the value that is added to the goods and services by different institutions belonging to that sector/industry in the process of production. In other words, the value-added is the net output of the sector after adding up all its outputs and subtracting the intermediate inputs. The value-added of

Table 5
The centrality of Iran's big industrial plants.

Industrial plants	Degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality	Value-added coefficients
Manufacture of chemicals and chemical products	87.11	158.44	0.5634	0.81	28.30
Manufacture of basic metals	80.59	125.61	0.5633	0.72	21.25
Manufacture of motor vehicles, trailers and semi-trailers	66.13	97.58	0.5631	0.64	12.55
Manufacture of non-metallic mineral products	51.08	61.78	0.5630	0.54	8.41
Manufacture of food products	48.23	56.23	0.5550	0.51	8.70
Manufacture of machinery and equipment	45.29	52.91	0.5544	0.50	8.1
Manufacture of pharmaceuticals	42.87	50.52	0.5543	0.43	3.35
Manufacture of rubber and plastics products	41.36	45.33	0.5542	0.40	2.07
Manufacture of computer and electronic products	36.64	40.12	0.5540	0.33	0.49
Manufacture of leather products	35.18	38.61	0.538	0.28	0.08

Table 6
The centrality of Iran's major economic sectors.

Economic sectors	Degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality	Share in the value-added
Services	76.53	140.19	0.559	0.77	56.8
Manufacturing and mining	61.54	91.34	0.5583	0.59	19.5
Oil	50.23	70.28	0.5578	0.52	11.6
Agriculture	42.19	49.26	0.533	0.41	10.3

each sector determines that sector's growth rate. The coefficients of value-added of each plant show the share of each series of activities in the value-added created by large industrial plants in Iran. The required data is collected by data collectors visiting the industrial plants and completing questionnaires. After various control and validation stages, the results obtained are reported as an industrial statistical survey by the Statistics Office of the Central Bank.

As per the table, industries with higher value-added coefficients have a higher centrality. This statement also applies to major economic sectors. Table 6 has sorted the four major economic sectors based on the centrality criteria. In addition, a separate column presents the share of each sector in the value-added of the total economy in the studied years (March 21, 2014 to March 21, 2017).

Tables 5 and 6 reveal some interesting findings. First, industries centrality in a stock network is representative of power and the position of the corresponding industry in the entire market. The chemical manufacturing industry has a higher value-added coefficient and is therefore more central in comparison to the other industries and this finding implies the more powerful relationship among the chemical manufacturing industry stocks in the network. Although the performance of traditional industries such as the leather industry is weak, chemical and petrochemical products comprise one of Iran's most important exports. The stocks in this industry have therefore become more active and interesting for investors and this turn of events has given them a higher centrality in the stock market network.

To assess the significance of the relationship between the study variables, the results obtained from Pearson's and Spearman's correlation tests are presented in Table 7. The results of these tests confirm the positive and significant correlations between β-CAPM and centrality and also between the value-added coefficients and centrality.

4. Discussion and conclusion

The stock market is a complex system in which complex relationships exist among stock price fluctuations. From a financial perspective, stock correlation networks have been developed to exhibit the system complexities and the market dynamics. Studying the stock market using complex networks facilitates the understanding of correlation patterns among stocks, and therefore provides an appropriate guideline for risk management, asset allocation and stock pricing mechanism. In the present article, the correlation network of Tehran Stock Exchange was created using the threshold method, and centrality in the network was measured based on the four centrality criteria (degree, betweenness, closeness, and eigenvector centralities). The results of the assessment of the stocks' centrality showed that stocks with a higher market capitalization, larger transaction volume and higher price fluctuations are more central. The price fluctuation of

Table 7
The results of the correlation tests.

	Degree centrality	Betweenness centrality	Closeness centrality	Eigenvector centrality
β-CAPM[a]	0.22 (0.00)	0.12 (0.04)	0.22 (0.00)	0.24 (0.00)
Value-added of industries[b]	0.98 (0.00)	0.98 (0.00)	0.98 (0.00)	0.98 (0.00)
Value-added of economic sectors[b]	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)	1.00 (0.00)

P-values are reported in parentheses.
[a]Correlation test is Pearson.
[b]Correlation test is Spearman.

stocks can occur due to changes in factors such as economic factors, factors related to the company and industry and factors related to the investors and the stock traders in the market. Nevertheless, these price fluctuations are more severe for the more central stocks. In other words, more central stocks are exposed to more shocks, since they are linked to more stocks, and their price is therefore not only affected by their relevant company and industry, but also by other stocks' price changes (due to factors specific to that particular stock's company/industry). These stocks therefore have greater price fluctuations and consequently bear a higher risk. Examining the relationship of centrality with β-CAPM and the Sharpe ratio showed that the more central stocks are bonds that bear a higher systematic risk. These findings are consistent with the results obtained by Pozzi et al. [76] and Qiao et al. [77]. The results of the centrality assessment divided by industry showed that industries with a higher value-added coefficient are positioned in a more central area of the network. In addition, major economic sectors with a higher growth are also more central.

Such correlation shows that the stocks belonging to a growing industry or a growing economic sector of the whole economy have stronger network relationships, because, with one industry's or economic sector's booming and its increasing demand, its stock prices will tend to rise, and a price co-movement will be observed among the stocks belonging to that industry or sector (an ascending movement). In addition, the stocks belonging to industries affiliated to that growing industry will behave similarly, thereby increasing the price co-movement among the stocks of the affiliated industries and the stocks belonging to the growing industry itself. The correlation of the growing industry's stocks with each other as well as with other affiliated stocks will therefore increase and stronger network relationships will be observed. As a result, in the Iranian stock market network, sectoral growth can be somewhat reflected in the level of relationships among the stocks belonging to that sector. It is worth noting that this finding is not inconsistent with the idea that networks contract in times of crisis [78], because when there is growth in an industry or a sector, only their affiliated industries are stimulated and not the entire network; however, in the case of a crisis, a deep, long and pervasive recession occurs that affects all industries and economic sectors. The present findings at the level of industries are consistent with the results obtained by Ahern and Jarrad [79], who used the business flow data of 479 American industries to construct a network and found that the more growing industries are more central, and also with the results obtained by Chen et al. [80], who constructed the stock market network of China. The results of the present article are robust based on the robust checks conducted, including considering different measures of centrality and different specifications stipulations.

The present findings can have implications both for theory and practice. Theoretically, the introduction of complex network analysis can reveal particular aspects of the Arbitrage Pricing Theory (APT) model and thus propose a new APT model that includes factors related to stock interactions and also the relationships between industries and stocks. Stock market analysis based on complex networks can help put this theory into practice. Based on the findings of this study, centrality contributes to market risk exposure, and thus provides a micro foundation for market βs. Alternatively, if the four-factor model in APT is deficient, centrality can reflect the manifestation of an omitted factor. Centrality can therefore act as a proxy for the unknown factor of market risk or as a characteristic for the market β. In addition, traditional asset pricing models are mainly defined on the basis of the particular features of the asset itself, and considering inter-stock effects with the centrality criterion can help enrich these models.

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Appendix

See Table 8.

Table 8
List of companies.

Ind. & M. L.	Azarab	Shahroud Sugar	Dasht Morghab	Iran Casting
Margarin	Iran Mobil Tele	Khoy Sugar	Iran Radiator	Iran Chemical Industries Inv.
Niromohareke M.	Offset	Ghandi Cables	Rayan Saipa	Sepehr Novin
Bahonar Copper	Alborz Darou	Razi P. Glasses	Rouz Darou P.	Firooze ETF
Bafgh Mining	E. Kh. Shargh	Hamadan Glass	I. T. Foundry	Kerman Tire
Iran Zinc Mines	Ama	Daroupakhsh	Zamyad	Butane Group
Iran Mineral P.	Iran Tire	Sina Chem. Ind.	Salemin Factory	Behshahr Ind.
Magsal Agri.	Iran Transfo	Fars Chem. Ind.	Saipa Azin	Fars Dev.
N. I. L. Z.	Iran Khodro	Khalij Fars	Saipa Glass	Iran Parenteral
I. N. C. Ind.	Iran Darou	Kermanshah Petr.	Sobhan Pharm	Pars Refract.
Daroupakhash I.	Iranmerinos	Qayen Cement	Sepanta	Iran Mineral P.
Motorsazan	Irka Part	Kordesta Ce. Co.	Sakht Ajand	Iran Ferr.
Motogen	Abadgaran	Kerman Cement	Iran Motorcycle	Zar Spring
Mahram Mfg.	Absal	Hormozgan Cem.	Alborz Inv.	Amirkabir Steel
Mehrcam Pars	Bama	Hegmatan Cement	Omid Inv. Mng.	Iran Fold
Petr. Tran.	Ansar Bank	Sina Darou Lab.	Iran Kh. Inv.	Khouz. Steel
Behran Oil	Bank of M.E.	Tuka Trans.	Atye Damavand	Mobarakeh Steel
Pars Oil	Karafarin Bank	Iran China Clay	Buali Inv.	Khorasan Steel Co.
Spahan Naft	Behceram	Inf. Services	Bahman Inv.	Iran Auto-Parts
Aluminum R.	Gorji Biscuit	A. I. S. D.	Pars Tousheh	Isfahan Sugar
R. Mill Prod.	Alborz Bimeh	DPI	Ir.Inv.Petr.	Piranshahr S.
Tehran Const.	Asia Bime	Abouraihan P.	Pardis Invsetment	Sabet Khorasan
Nirou Moharreke	Parsian	Osvah Pharm.	Toosgostar Inv.	Shirin Khorasan
Nirou Trans	Dana Insurance	Exir Pharm.	Azarbayjan Inv.	Ghazvin Sugar
NiroCholor	Bime Ma Co.	Amin Pharm.	Iran Ind. Dev.	Lorestan Sugar
Hamkaran System Co.	Mellat Insur.	Jaber Hayan P.	Metals & Min.	Neyshabour S.
Saba Noor	Pars Int. Mfg.	Razak Lab.	Iran N. Inv.	Hegmatan Sugar
Tidewater	Pars Khazar	Zahravi Phar.	Tamin Daroo	Alborz Cable
Parsian Ecommerc	Pars Khodro	Farabi Pharm.	Rena Investment	Etebari Iran Co.
Iran Tractor	Pars Darou	Loghman Pharm.	Iran Const. Inv.	Iran Carton
Technotar	Pars Ceram	Kowsar Pharm.	Saman Gostar	Daroupakhsh P.
Techinco	Pars Switch	Derakhshan Teh.	Saipa Inv.	Alvand Tile
Jaam Darou	Pars Minoo	Sobhan Pharm.	Sepah Inv.	Pars Tile
Yazd Jooshkab	Paxan	Khazar Cement	Shahed Inv.	Takceram
Chadormalu	B.A Oil Refinie	Khoozestan CE.	Pension Fund	Saadi Tile
Charkheshgar	Tabriz.Oil.Refine	Darab Cement	Insurance Inv.	Sina Tile
North Drilling	Isf. Oil Ref. Co.	Doroud Cement	Ind. & Mine Inv.	Calcimine
Fajr Petrochemical	Palayesh Tehran	Sepahan Cement	Ghadir Inv.	Iran Carbon
Fanavaran Petr.	Pardis Petr.	Shahroud Cement	Behshahr Group	IRI Marine Co.
Mobin Petr.	Jam Petr.	Shargh Cement	Bank Melli Inv.	Iran Combine
Iran Glass Wool	Khark Petr.	Shomal Cement	Maskan Invest.	Kavir Tire
I. Pegah Dairy	Petro. Inv.	Gharb Cement	Housing Inv.	Chimidarou
W. Azar. Pegah	Shazand Petr.	Siman Fars Noe	Melat Inv.	Bahman Group
Plascokar Saipa	Shiraz Petr.	F. & Kh. Cement	Tosee Melli Inv.	Paksho
Pumpiran	Farabi Petr.	Fars Cement	Oil Ind. Inv.	Melli Ind. Grp.
Sand Foundry	Nirou Inv.	Banks Employees	Parsian Oil&Gas.	Pars Shahab
Isfahan Cement	Ardekan Ceramic	Iranian Lizing	Gol-E-Gohar.	Lamiran
Bojnourd Cement	Cement INV. Co.	Ghadir Kh. L.	Goltash	Loabiran
Behbahan Cement	Oroumiyeh Cem	Sahand Rubber	Glucosan	Iran M. & P. M.
Khash Cement				

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