Advances in Mathematical Finance & Applications, 6(3), (2021), 465-477
DOI: 10.22034/AMFA.2019.1873319.1258

Published by IA University of Arak, Iran
Homepage: www.amfa.iau-arak.ac.ir

The Effect of JCPOA on the Network Behaviour Analysis of Tehran Stock Exchange Indexes

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ARTICLE INFO
Article history:
Received 10 July 2019
Accepted 16 October 2019

Keywords:
Network Analysis
MST
Hierarchical Clustering
Correlation distribution
JCPOA

ABSTRACT
The purpose of this paper is network behaviour analysis of Tehran Stock Exchange indexes using the minimum spanning tree (MST) and hierarchical clustering. Network analysis by simplifying a complex system allows for the extraction of important and essential information from that system. In this paper, using network analysis the simultaneous behaviour of 38 industry indexes in Tehran Stock Exchange in manufacturing, service and investment sectors during 2011-2017 was investigated. These analyses included identifying the main indexes in the direction of moving other indexes using the MST, providing a classification using hierarchical clustering for the behavioural similarity of the indexes as well as examining the degree of integration (behavioural similarity) of market indexes over time. The results showed that investment, automobile, industry and medicine indexes in the research period had a major role in guiding other indexes and indexes can be classified into six groups in terms of behavioural similarity. The market has also been moving toward integration of indexes since early 2015 and beginning the executive steps of Joint Comprehensive Plan of Action (JCPOA). This reflects the investors' hope for the promotion of all indexes.

1 Introduction

In the real world, there are many systems that can be described by the help of complex networks. The system of cities in a country whose connection is through the roads is an example of these networks in which distance plays a major role to connect the cities of that country. Therefore, cities with lower distance have higher communication levels and they influence each other, or the city that connects a large number of cities plays a key role in the system. As an example of networks in the field of economic and finance, stocks in a stock market or oil-exporting countries can be considered as members of a system in which the two-member relationship is considered as the correlation of the price of these two.

The complexity of the system means that there is a large amount of information in the system which can challenge the extraction of the basic and useful information of the system. Accordingly, approaches are needed to maintain basic and decisive relationships in addition to simplifying system and

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minimizing complexity. One of these approaches is network analysis by the help of graph theory. Network analysis shows the characteristics of the market, which simulation and factor analysis methods can not reveal [1]. Therefore, in this paper, the behavior of the industry indexes of the Tehran Stock Exchange is investigated using the network analysis. By this analysis, the relationships and behaviors in this system are explained. The issue that has been addressed in this study is that there are 38 indexes for various industries in the Tehran Stock Exchange which are calculated and announced daily for various industries [29, 32].

The question is that if the behavior of these 38 indexes is considered as a network that is inside the system of the Iranian stock market and different factors such as economic sanctions, regional conflicts, and economic and political decisions of the government influence on the rates of these indexes, what the behavior of these indexes is during different periods? The other question is that movement of which indexes influence on movement of other indexes? All of these questions motivate researcher to seek answer for this question: what is the network analysis of Tehran Stock Exchange Industry indexes behavior using MST and hierarchical clustering? The rest of the paper is organized as follows. Section 2, in detail, describes the theoretical background including MST, stock market network structure and hierarchical clustering. In section 3, the methodology including sampling, procedure, and data analysis is raised. In section 4, the numerical data is employed to illustrate the validity and significance of the model. In section 5 and 6, discussion and conclusion were brought.

2 Theoretical Background

In this section, MST, stock market network structure and hierarchical clustering are introduced and a literature review of them is presented.

2.1 Minimum Spanning Tree

A graph or network G is a regular pair such as (V, E) in which V is a finite and non-null set, and E is a subset of all two-member subsets of V. The members of V are called vertices and the members of E are called edges of G. Graphs are used to solve many problems in mathematics and computer science. Many structures can be displayed using graphs [26, 28]. The MST (for the weighted connected graph) means a tree that the total weights of its edges has the least possible value among all of its spanning trees. Since MST is a tool that frees the network from complexity in addition to maintaining the basic relationships of the indexes by calculating the minimum possible distances between the indexes, it has been used in the analysis of the stock market, the foreign exchange market and oil market. Coletti [2] has compared the MST of the Italian stock market. In this research, a network of 100 Italian companies was created during 2001-2011 using four different methods.

Obtained MST was compared based on methods and industry sectors. The results showed that several sections corresponded to the network cluster, while the rest, especially the business and clothing departments are scattered. Yang, Zhu [3] calculated the correlation coefficient of stock based on the MST. In this study, the data related to the daily closing price of 268 stocks forming the S & P500, 221 stocks of the London Stock Exchange and 148 stocks of Shanghai were used. The results showed that, at first, both the average of mutual information and the standard deviation of mutual information distribution gradually increased for all stock markets to reach the peak and eventually decreased. Ji and Fan [4] examined the oil price integration of oil-exporting countries using graph theory and concluded that the market was moving towards integration before the global crisis of 2008. The results also showed that the geographic location of countries and their geographic proximity lead to price similarity.

2.2 Stock Market Network Structure

In recent studies, special attention has been paid to the network structure in various fields, and useful information has been attained by studying a system with network structure. The network structure of financial markets is also a subject that has recently been investigated and has been found to be useful in analyzing the stock market network. Several attempts have been done to have network analysis of a specific stock market, particularly on the New York Stock Exchange [5-8] and other countries' exchanges [9-16]. You, Fiedor [17] implemented a network analysis on the Shanghai Stock Exchange. Eom, Oh [18] reviewed the topological properties of stock networks based on the MST and random matrix theory in financial time series.

2.3 Hierarchical Clustering

In data mining and statistics, hierarchical clustering is a method of cluster analysis which seeks to build a hierarchy of clusters. In general, the merges and splits are determined in a greedy manner. The results of hierarchical clustering are usually presented in a dendrogram [19]. Mantegna [20] investigated hierarchical structure of stocks in financial markets. Tumminello, Lillo [21] proposed a method to obtain hierarchical trees, correlation based trees and networks from a correlation matrix in financial markets. Bhattacharjee, Shafi [22] investigated the dynamics of cross-market clustering and connectedness of the Asian capital markets. Kantar, Deviren [16] examined the hierarchical structures of Turkey's foreign trade by using real prices of their commodity export and import move together over time.

Table 1: The index number and the name of index.

	Name	NO.	Name	NO.	Name
1	Mass Housing	14	Food products	27	Medical instruments
2	Banks	15	Non-metallic minerals	28	Radio
3	Electric devices	16	Transportation	29	Computers
4	Insurance and retirement	17	Paper products	30	Industry
5	Multi field's industrial	18	Metal minerals	31	Investments
6	Publishing and printing	19	Tile and ceramic	32	Other financial
7	Leather products	20	Automobile	33	Other mines
8	Wood products	21	Rubber	34	Chemical
9	Pharmaceutical materials	22	Metal products	35	Cement
10	Extraction of oil	23	Financial	36	Communication devices
11	Technical and engineering	24	Textiles	37	Agriculture
12	Basic metals	25	Machinery	38	Coal
13	Sugar and lump sugar	26	Petroleum products		

3 Research Methodology

3.1 Sampling

The statistical population consisted of the companies listed in the Tehran Stock Exchange, which were categorized into 38 industries. In this paper, 38 industry indexes from Tehran Stock Exchange were considered in the period from the beginning of 2012 to the end of 2017. The data was extracted using the Rahnavard Novin 3 software and MATLAB software was used to analyze them. Table 1 presents the name of 38 industry indexes in Tehran Stock Exchange.

3.2 Procedure

The network investigated in this study was a network of 38 industry indexes of Tehran Stock Exchange. These 38 indexes were considered as 38 vertices of graph and these vertices are interconnected two-by-two. The complete graph was obtained with 38 vertices which include 703 edges. The edge weight between index i and index j was the same Pearson correlation coefficient between the weekly return rate of the two indexes i and j. This complete graph is the same network with complete connection which does not provide useful information with this volume of complexity. In a network in which its vertices are indexes of the stock market industry and the weight of each edge represents the correlation between the available edges in the head of both edges, firstly, the MST simplifies the system and, then, it provides the possibility to understand the most important relationships (coherent behavior of the indexes) contained in the system.

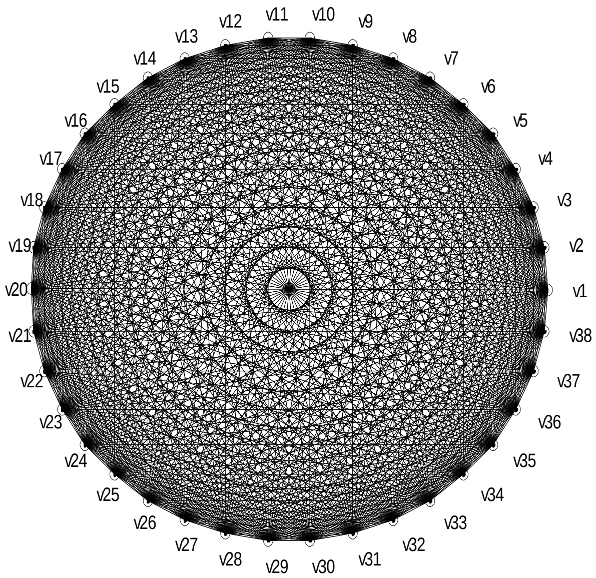

Fig. 1: Complete graph with 38 vertices

Constructing the MST, we first need to convert the correlation matrix C into a ‘distance’ matrix D. Following Mantegna (1999) and Mantegna & Stanley (1996), we use the non-linear mapping:

$$d_{ij} = \sqrt{2(1-\rho_{ij})} \quad (1)$$

Getting the elements d_{ij} of D. Since$-1 \leq \rho_{ij} \leq 1$, we have $0 \leq d_{ij} \leq 2$. This distance matrix D can be thought of as representing a fully connected graph with edge weights d_{ij}. In the terminology of graph theory, a ‘forest’ is a graph where there are no cycles [23]. A ‘tree’ is a connected forest. Thus, a tree containing n nodes must contain precisely n 1edges [23, 24]. The MST T of a graph is the tree containing every node, such that the sum $\sum_{d_{ij} \in T} d_{ij}$ is a minimum. There are two methods for constructing the MST-Kruskal's algorithm and Prim's algorithm [6]. We used Kruskal's algorithm, details of which are given in [25]. For a MST with d_{ij} weights, ultrametric space d^*_{ij} between vertex i and j can be identified as the maximum value of the Euclidean distance d_{kl} by moving in single steps from vertex i to j in the MST. The MST and ultrametric space are equal [27]. It means that there is an ultrametric space for each tree and exactly there is a tree corresponds to each ultrametric. With the help of obtained ultrametric by the MST, a hierarchical cluster can be constructed to reveal the internal cluster relationship of indexes and the near-dispersed connections between them. Hierarchical cluster helps to achieve the overall structure and main risks of the market.

3.3 Data Analysis

After calculating the MST, the relationships between the indexes are determined. Index degree, Betweeness Centrality of index and index farness are examined and computed to achieve a quantitative criterion for investigating the importance of indexes in the MST.
i. Index degree: The degree of an index in the MST is the number of edges in that index. Therefore, K(i), the index degree of ith, is calculated by the formula of $K(i) = \sum_{j=1}^{n} a_{ij}$. If the indexes i and j are interconnected by an edge in MST, $a_{ij} = 1$ and otherwise $a_{ij} = 0$. n is the number of indexes in the MST. When the vertex degree for an index becomes high, it indicates the importance and strength of the index in directing other indexes.

ii. Betweenness centrality of index: Sieczka and Hołyst [30] identified between centrality as an important and useful measurement for determining the centrality of the index. This index is calculated as follows:

$$B(i) = \frac{2}{N(N-1)} \sum_{(j,l)} \frac{\sigma_{jl}(i)}{\sigma_{jl}} \quad i \neq j \neq l \tag{2}$$

Where, $B(i)$ is the betweeness centrality of the ith index, $\sigma_{jl}(i)$ is the number of shortest paths from j to l passing through i and σ_{jl} is the number of shortest paths from j to l. The betweenness centrality for constructed MST will be computed. Since the shortest path in the MST for each pair of vertices is unique, the value of $\frac{\sigma_{jl}(i)}{\sigma_{jl}}$ is zero if the transient path from j to l does not pass through i and it is one if it passes through i. $B(i)$ reflects the amount of degree that other indexes rely on i index. The higher value of $B(i)$ represents the higher betweenness centrality.

iii. Farness of index: Sabidussi [31] defines the notion of index farness ith as the sum of the distances of that index to all other indexes. Therefore, $\text{Farness} = \sum_{(i,j)} R_{ij} \ i \neq j$. Where R_{ij} is the shortest distance from i to j in the MST. The lower amount for ith index farness indicates that the degree of market centrality i is higher in all indexes and the market i is closer to other indexes. Being in the between centrality of index and index farness are more important than the index degree because they also consider the weights of the edges.
In the following, several dynamic scales are presented for the MST in order to evaluate the evolution and integration of the indexes over time. Furthermore, in order to investigate the evolution and integration of indexes over time, two dynamic scales of correlation distribution and normalized tree length are presented for the MST.

a: Correlation distribution: Onnela, Chakraborti [6] defined the dynamic mean of correlation and the dynamic variance of correlation using the matrices of the correlation coefficient of the indexes in the clusters as follows.

$$\bar{C}(t) = \frac{2}{N(N-1)} \sum_{(i,j)} C_{ij}(t) \tag{3}$$

$$Var(t) = \frac{2}{N(N-1)} \sum_{(i,j)} (C_{ij}(t) - \bar{C}(t))^2 \tag{4}$$

$\bar{C}(t)$ is the mean of correlation coefficient, $C_{ij}(t)$ is the correlation coefficient between index i and j in t^{th} cluster. When the mean becomes higher and the variance has low changes, this indicates that the index is more integrated over time.

b: Normalized tree length: Onnela, Chakraborti [6] introduced the normalized tree length as an appropriate index for investigating the integrity of the indexes which is calculated as follows:

$$L(t) = \frac{1}{N-1} \sum_{e_{ij} \in MST} e_{ij} \tag{5}$$

In which $L(t)$ is the normalized tree length, $N - 1$ is the number of edges in the MST and e_{ij} is the edge in the MST. If $L(t)$ becomes smaller over time, it shows that the integrity of the indexes has increased and the coordination between prices has been improved.

4 Research Findings

4.1 The MST Obtained from the Network Structure

At first, industry indexes were extracted from websites related to Tehran Stock Exchange during the period of 2012-2017. Then, the weekly return (five days in each week) was calculated for all indexes. 300 weekly return rates were yielded for each index. Using Kruskal's algorithms, the MST was calculated for network structure of stock indices and is shown in Fig. 2. The tree is such that minimum d_{ij} (maximum correlation) is between the vertices or the same indices.

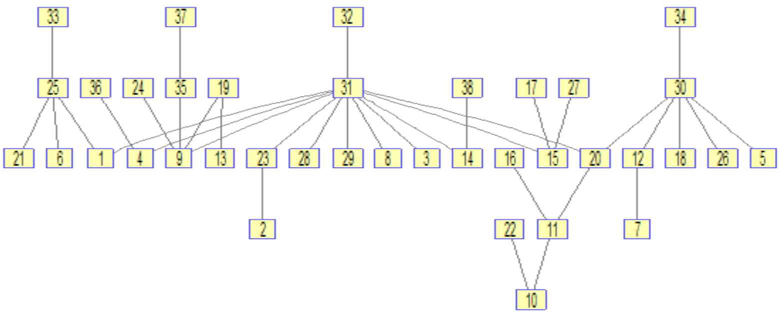

Fig. 2: MST obtained by 38 indexes

The resulted MST has vertices, edges and d_{ij} weights, as shown in Table 1. The weight d_{ij} shows the correlation between the two vertices. If this weight becomes closer to $\sqrt{2}$, it indicates a weak relationship and if it becomes closer to zero or 2, it shows a stronger relationship. MST vertices are the same 38 industrial indexes which are connected to each other in Table 2 by the brought edges. Furthermore, the weight of each edge which indicates the correlation between the edges is brought. For example, the edges (1.25) indicate that between the vertex 1 (the index of Mass Housing) and vertex 25 (machinery) is an inevitable relationship. The strength of this relationship (the weight of this edge) equals 1.0128, which shows a relatively weak relationship between the two indexes.

Table 2: MST edges and weights.

Edge	**Weight (d_{ij})**	**Edge**	**Weight (d_{ij})**	**Edge**	**Weight (d_{ij})**
(1, 25)	1.0128	(9, 35)	0.9404	(20, 30)	0.1747
(1, 31)	0.8064	(10, 11)	0.9456	(20, 31)	0.6636
(2,23)	0.1274	(10, 22)	1.0460	(21, 25)	1.0722
(3, 31)	1.0248	(11, 16)	1.2268	(23, 31)	0.6089
(4, 31)	1.0252	(11, 20)	0.8808	(25, 33)	1.1401
(4, 36)	1.2813	(12, 30)	0.6960	(26, 30)	0.9664
(5, 30)	0.6073	(13, 19)	1.2103	(28, 31)	0.9395
(6, 25)	1.2099	(14, 31)	0.9445	(29, 31)	1.0263
(7, 12)	1.2867	(14, 38)	1.1206	(30, 34)	0.7058
(8, 31)	1.1882	(15, 17)	0.9595	(31, 32)	0.7590
(9, 19)	1.0308	(15, 27)	1.2263	(35, 37)	1.2191
(9, 24)	1.2123	(15, 31)	0.9291		
(9, 31)	0.9529	(18, 30)	0.7346		

Table 3: Indexes ability measurement criteria in influencing and directing other indexes.

Index No.	Degree	Betweenness centrality	Farness of index	Index No.	Degree	Betweenness centrality	Farness of index
1	2	0.37553343	87.55053	20	3	0.89331437	74.26099
2	1	0	90.26021	21	1	0	156.5317
3	1	0	101.862	22	1	0	170.4928
4	2	0.10241821	99.8279	23	2	0.10241821	85.67471
5	1	0	100.3142	24	1	0	133.39
6	1	0	161.49	25	4	0.29871977	117.9341
7	1	0	148.4372	26	1	0	113.2444
8	1	0	107.7453	27	1	0	138.8478
9	4	0.47795164	89.74694	28	1	0	98.79196
10	2	0.10241821	132.8365	29	1	0	101.9185
11	3	0.29587482	100.686	30	6	0.56899004	78.45289
12	2	0.10241821	102.1162	31	12	1.61877667	64.9705
13	1	0	168.3643	32	1	0	92.29413
14	2	0.10241821	97.08341	33	1	0	158.9763
15	3	0.20199147	94.70182	34	1	0	103.8619
16	1	0	144.8494	35	2	0.10241821	121.7204
17	1	0	129.2435	36	1	0	145.9546
18	1	0	104.8971	37	1	0	165.6076
19	2	0.10241821	124.795	38	1	0	137.425

4.2 Investigating the Strength of Industry Indexes in Market Orientation

Examining the strength of indexes in market orientation, the values of the three criteria of degree, being in the between of centrality and farness are given in Table 3. Regarding degree column of each indexes, it is determined that among the indexes of different industries, investment index with 12 indexes (mass housing, insurance and retirement, pharmaceutical materials, financial, other financial, radio, computer, wood products, electric devices, food products, non-metallic minerals and automobile) were correlated. In other words, investment index was influential in directing these 12 indexes. Then, the index of industry with 6 indexes (chemical, automobile, basic metals, metal minerals, petroleum products and industrial multi-fields) was correlated. In other words, the industry index was influential in directing these 6 indexes. The machinery and pharmaceutical materials were influential in directing the other 4 indexes. Machinery index is associated with other mines, rubber, publishing and printing, and Mass Housing indexes. The pharmaceutical materials are associated with ceramic tile, cement, textiles and investment indexes. The indexes such as technical and engineering, non-metallic minerals and automobile indexes were each influential in directing 3 other indexes. Furthermore, the results of indexes of betweeness centrality revealed that the investment, automobile and industry indexes had higher centrality among the other indexes, respectively, and hence had higher effects in directing the other indexes. The results of index farness showed that the indexes of investment, automobile and industry had the least distance with other indexes, respectively, and therefore, had high influence in directing other indexes.

4.3 Clustering of Industry Indexes

By using ultrametric space, the classification of indexes based on behavioral similarity and the hierarchical cluster representation of them are presented in Fig. 3.

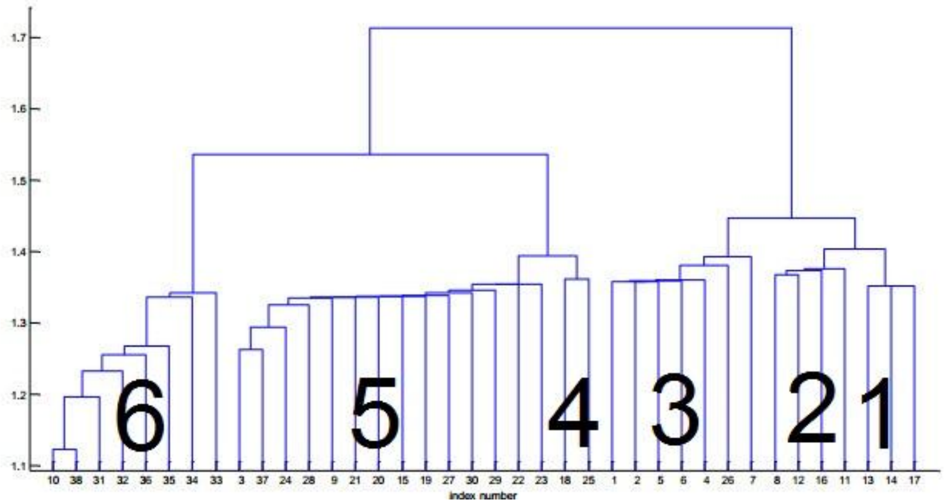

Fig. 3: Hierarchical clustering of various indexes

Accordingly, six main clusters can be considered.

First cluster: sugar and lump sugar, food and paper products

Second cluster: wood products, basic metals, transportation and engineering

Third cluster: mass housing, bank, insurance and retirement, industrial multi-fields, publishing and printing, petroleum products, leather products

Fourth cluster: metal minerals and machinery

Fifth cluster: electric devices, radio, computer, agriculture, pharmaceutical materials, metal products, automobiles, rubber, non-metallic minerals, ceramic tiles, medical instruments, industry, finance, textiles,

Sixth cluster: extraction of oil, coal, cement, chemical, other mines, investment, other finance, communication tools

The close relationship between each cluster can be justified on the basis of the nature of the index by paying attention to elements. For instance, putting sugar and lump sugar and food products in one category is because of their nature of being food orientation. Mass housing, bank, insurance and retirement are put into one category, which are interpretable as regards with the effect of bank interest rate on mass housing industry. Metal minerals and machinery are put in the similar behavioral group, which are justifiable by the consumption of metal in the machinery industry.

4.4 Investigating the Integrity of the Indexes Over Time

To examine the integrity of the indexes over time, the data were divided into 12 categories which 25 consecutive weeks are in. In Fig. 4 and 5, the chart of correlation dynamic mean, correlation dynamic variance and normalized tree length are shown.

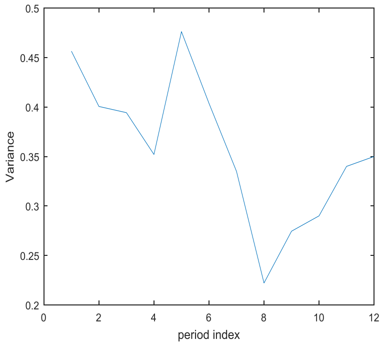

Fig. 4: Correlation dynamic variance

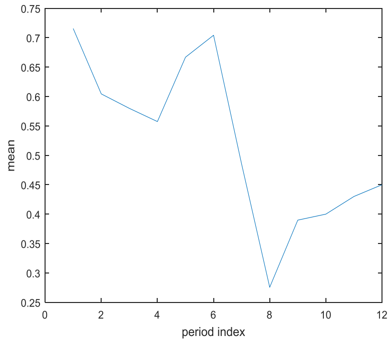

Fig. 5: Correlation dynamic mean

As shown in Fig. 4 and 5, from the beginning of 2015, dynamic mean of correlation which is available in MST, increased by passing the courses and coherent behavior of indexes was encouraged. On the other hand, slight changes of dynamic variance of correlation from the beginning of 2015 brought us to this result that from the beginning of 2015 in MST, the increase in correlations in most of edges happened. In other words, from the beginning of 2015, integrity between the indexes increased and the indexes had similar behavior in terms of price. The normalized tree length which is shown in Fig. 6 confirms this issue.

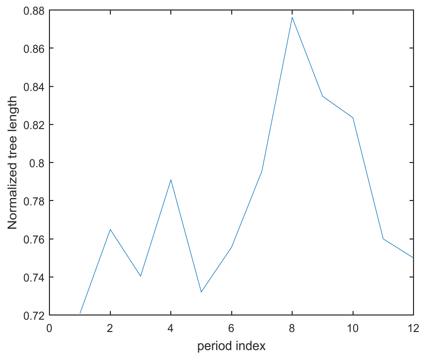

Fig. 6: The normalized tree length

Fig. 6 shows that since the beginning of 2015, the normalized tree length became smaller over the time. This suggests that the integrity of the indexes has increased since the beginning of 2015 and coordination between prices has enhanced.

4.5 Analysis and Discussion

The purpose of this paper was to analyze the network behavior of Tehran Stock Exchange indexes by using MST and hierarchical clustering. The network in which its vertices are industry indexes of the stock market and the weight of each edge represents the correlation of the two vertices on the both ends of the edge. In this paper, the coherent behavior of indexes in different time periods was investigated. For this purpose, one metric is defined on the network edges using a correlation coefficient; then, the MST and hierarchical clustering were calculated to reduce network complexity. Following that, the criteria of degree, between centrality and farness on the MST were calculated in order to identify the powerful and effective indexes in market orientation. Furthermore, stability and integration of indexes in the market were investigated using correlation dynamic mean, correlation dynamic variance and normalized tree length.

The results of the research showed that investment, automobile, industry indexes in the review period were the main indexes with the highest impact on the directing of other indexes. Indexes were categorized into sex categories based on behavioral similarity that was measured by the ultra-metric. The findings also revealed that, since early 2015 and the beginning of the implementation process of Joint Comprehensive Plan of Action (JCPOA), the market has been moved towards integration of indexes which indicates investors' hope for upgrading all of the indexes. Before that time, the integrity of the indexes has been decreased which suggests a different valuation of investors from the returns of different indexes. One unanticipated finding was that in the 6 clusters which were resulted as regarding the 38 indexes, the relationships between the indexes were determined to some extent. For instance, in the first cluster, the indexes of sugar and food product came along each other. In the third cluster, there were indexes of mass housing, bank, insurance and retirement and industrial multi-fields. In the sixth cluster, there were indexes of extraction of oil, coal, cement, chemical and other minerals. The other unexpected finding was that the effect of JCPOA in creating integrity between the indexes of different industries from the beginning of 2015 was shown.

5 Conclusion

The findings of this study suggest that investors should pay enough attention to network behavior of indexes. In each country, such as Iran, it is possible that the economic condition of the country be in a state of flourishing, normal, or stagnant and the investors' behavior tend to buy the stock of specific companies. The investors who have adequate research about the network behavior of indexes make decisions in their investments with more readiness and consequently minimize the investment risk. The findings of this study make several contributions to the current literature.

Firstly, the network was constructed whose edges were the indexes of Iran's stock market and the weight of each edge indicate the correlations between the available edges in the head of both edges. Secondly, a MST of the indexes of the Iranian stock market was calculated. Using MST and the criteria of being in the middle of centrality of index, index farness and index degree, the indexes which had high influence in directing other indexes were introduced. Thirdly, considering MST and ultrametric space, hierarchical clustering was done whose results were classifying 38 indexes in 6 clusters. The indexes in each of these clusters had similar behavior. Fourthly, using the criteria of the normalized tree length, correlation dynamic mean and the correlation dynamic variance, the integrity of the indexes was investigated in the period from 2011 to 2017.The findings in this report are subject to at least two limitations. First, the coherent behavior of indexes only in recent years was investigated. In different courses of time, the influential indexes can be different. If larger timeframe is selected, the interpretation of coherent behavior of indexes by attributing that behavior to course events becomes more difficult. Future researchers should focus their research on the network behavior of the stock market, foreign currencies as well as the oil field. Investors are encouraged to pay attention to the network behavior of industry indicators. By identifying the effective indicators, along with clustering structure of the indicators, one can monitor the price behavior of effective indicators at any given time, and by considering their price changes, one can predict the price behavior of indicators related to that cluster.

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