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Analysis of Iran Banking Sector by Multi-Layer Approach

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Abstract

Networks are useful tools for presenting the relationships between financial institutions. During the previous years, many scholars have found that using single-layer networks cannot properly characterize and explain complex systems. The purpose of this research is to introduce a multiplex network in order to analyze, as accurately as possible, all aspects of communication between banks in capital market of Iran. In this article, each bank represents a node and three layers of return, trading volume and market Cap have been presented for analyzing the idea of multiplex networks. We have used the Granger causality method to determine the direction between nodes. For understanding the topology structure of these layers, different concepts have been used. The research findings show that the value layer topology has a significant similarity with the trading volume layer. Also according to the measure of centrality it can be seen that the centrality varies in different layers.

Keywords: Banking Sector, Centrality, Complex System, Granger Causality, Multiplex Network.

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Introduction

Network analysis is an important tool for modeling complex systems (Gaiand Kapadia, 2010; Battiston, 2012). Researchers have been conducting various studies by the concepts of complexity during the past years (Namaki, 2011; Namaki, 2013). One of the most important markets that can be analyzed by network discipline is the banking sector. In network science, the interbank market is presented by directed and weighted graphs. Investigating the interbank networks and understanding their systematic importance makes us look for an appropriate analysis method.

By extension of researches on complex networks, scholars have concluded that networks based on one type of relations cannot properly characterize and explain complex systems (Aldasoro and Alves, 2018; Borboa, 2015).

Especially, the relation between two banks is more complex than the information that can be summarized in one concept such as network direction (Bargigli, 2016).

There is widespread communication between different banks, each of that relates to a class of claims or markets (Bargigli, 2014; Bargigli, 2016).

We use multiplex networks to identify the characteristics of banks in the capital market. Multiplex Networks (Figure 1b) are special types of Multilayer Networks (Figure 1a) (Boccaletti, 2014). They consist of different layers and nodes (in this research Banks) that are identical in all layers, and each layer is based on one type of relationship (in fact each layer is a type of relationship) (Aleta and Moreno, 2018).

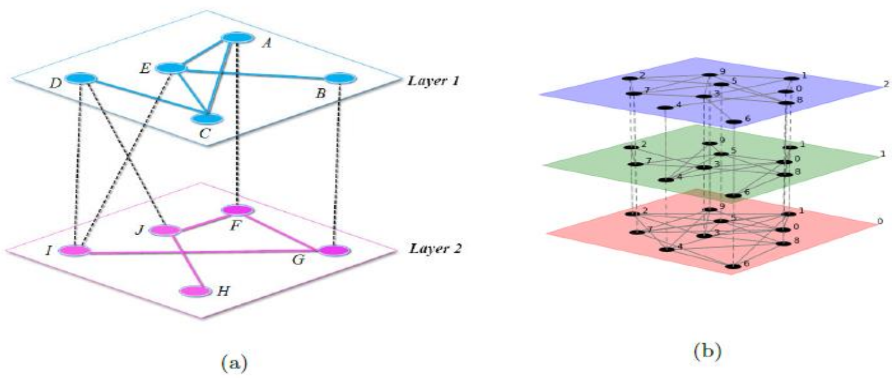

Figure 1. Multilayer (a) and Multiplex (b) network

Once the layers of the capital market are formed using multiplex networks, we will proceed to examine the topology of each layer separately. We will use Granger causality to determine the direction and weight in each layer (Tang, 2019; Caraiani, 2013).

Finding the characteristics of each layer, we can concentrate on important features of the multiplex network such as centrality (Bargigli, 2016). In networks, choosing the central or middle vertices is crucial in determining the network topology (Shirazi, 2013). Generally, a function that assigns numeric values to different elements in a network is called centrality.

There are different centrality measurers for evaluating network elements, some of them are defined on vertices and others on network edges (Zheng, 2012; Junker and Schreiber, 2008). Generally, the centrality of a node in a network is a criterion of node importance (Bargigli, 2016). In this study, centralities are devoted to the evaluation of network nodes. Node centrality is essential for identifying the most important nodes in any network architecture. The three most commonly used methods for measuring centralities are degree Centrality, Betweenness Centrality, and Eigenvector Centrality, which have all been calculated in this paper. Identification of central banks in the different layers and the whole layer is one of the essential achievements of this study. These banks are the source of contagion in financial markets. So, in order to prevent a financial contagion, it is important to identify these central banks (Kermarrec, 2011; Yu and Fan, 2015).

Until now, most researches in the complexity science are based on the analysis of single-layer networks. Multilayer networks have not been widely used in the economy discipline. Also, domestic market studies have not analyzed the financial markets using multiple networks. Bargigli et.al have investigated the structure of the Italian interbank market using multiplex network approach. They have analyzed the financial networks based on two different layers of maturity and the type of contract (Bargigli, 2014). Molina et.al has studied the relationship between Mexican banks through the multilayer network approach (Borboa, 2015). Eldaroso et.al have considered large European banks by maturity and instrument type to describe the main features of a multiplex network (Aldasoro and Alves, 2018). Using different types of interbank exposures, Cont et.al have investigated the systemic risk in the Brazilian market and the potential contagion contamination (Cont, Moussa and Santos, 2010). In this research seventeen listed banks of Tehran Stock Exchange have been analyzed from March 2016 to March 2019. The three listed banks, Sarmayeh, Iran Zamin and Qarz-al-Hasaneh Resalat were not considered due to the low trading days. This research organized in 4 sections. In part 2 the statistical models and methods will be defined. Data analysis and implementation of statistical models are considered in section 3. Section 4 has been dedicated to conclusions.

Methods

1. Detrending Data

In order to eliminate potential trends from daily trading volumes and trading value data, we use regression on a quadratic function of time. The quadratic function includes linear and nonlinear time trends in data (Andrew and Wang, 2000, Chen, Firth and Rui, 2001)

$$x_t = \alpha + \beta_1 t + \beta_2 t^2 + e_t$$

Here x_t is the raw data and e_t denotes the residuals.

2. Hsiao Granger Causality Test

Granger (1969) proposed an idea to better and more accurately estimate variables based on their relationships with their past quantities. The main drawback of the standard Granger Causality Test is the sensitivity to the choice of interrupt length, so that different interrupt lengths will, in most cases, yield different results. Therefore, Hsiao (1981) proposed a systematic self-explanation method for solving this problem to select the optimal interval length for each variable.

The selection of the optimal interrupt length is performed in two stages using the Hsiao Granger causality test method. In the first step, a set of self-explanatory regressions on the dependent variable is estimated. In the regression equations of this step, the dependent variable starts from one lag, and then subsequently another lag is added to each regression. It is advisable to add as many lags as possible. Estimated regressions will be as follows:

$$Y_t = \alpha + \sum_{i=1}^{m} \beta_i Y_{t-i} + \varepsilon_{1t} \tag{1}$$

After estimating all regressions, the final prediction error (FPE) criterion for each regression equation is calculated based on the following relation:

$$FPE(m) = \frac{T+m+1}{T-m-1} \cdot \frac{ESS(m)}{T} \tag{2}$$

In this formula T is the sample size and ESS is the sum of squares of the residuals.

The interval that meets the minimum FPE criterion will be the optimal interval length (m*). By setting m*, the first step of the test is completed. In the second step, the other variables with lags are entered into the regression equations. These regression equations are defined as:

$$Y_t = \alpha + \sum_{i=1}^{m^*} \beta_i Y_{t-i} + \sum_{j=1}^{n} \gamma_j X_{t-j} + \varepsilon_{2t} \qquad (3)$$

Then the final prediction error criterion for each regression equation is calculated by the following method:

$$FPE(m^*, n) = \frac{T + m^* + n + 1}{T - m^* - n - 1} \cdot \frac{ESS(m^*, n)}{T} \qquad (4)$$

The interval length that minimizes the final predictive error criterion (FPE) is the optimal interval length X. In the Hsiao Granger Causality Test, FPE (m*) is compared with FPE (m*, n*). If FPE (m*, n*)>FPE (m*), X_t is not the cause of Y_t, and if FPE (m*, n*) is <FPE (m*), X_t is the cause of Y_t. In the Hsiao Granger Causality Test, all variables are required to be stationary and if the variables are non-stationary, their first stationary difference must be used to perform the test.

3. Topology measures

3.1. Strength

The strength of a node is as follows:

$$w_i = \sum_{j \in \Psi(i)} w_{i,j} \qquad (5)$$

Where $\Psi(i)$ is the neighborhood set of node i. we consider $w(e_{ij}) = w_{ij}$ as the strength of edge (i, j).

3.2. Reciprocity

In direct networks, such as interbank networks, it is appealing to measure the likelihood of occurring double edges with opposite directions between two specific nodes. For calculating the reciprocity, there are different methods (Newman, 2002) .One of the reference formula for calculating the reciprocity is based on the correlation coefficient between matrix A and A^T, and the equation is as follows (Soramaki, 2007):

$$\rho = \frac{\sum_{i \neq j}(a_{ij} - \bar{a})(a_{ji} - \bar{a})}{\sum_{i \neq j}(a_{ij} - \bar{a})^2} \tag{6}$$

$\bar{a}$ is the average value of inputs A.

3.3. Density

The simplest measure for directed graphs is density. This is the ratio of the number of edges in the network to the number of possible edges representing the network density index and always between zero and one. This measure is defined as follows:

$$d = \frac{l}{n(n-1)} \tag{7}$$

Where n = |V|, l = |E|, V is the vertex or node set and E is the edge or link set (Bargigli, 2014).

3.4. Clustering coefficient

The clustering coefficient indicates how closely the vertices around the target node are interconnected, and measures the probability that the node or vertices belong to a specific cluster. The directed clustering coefficient of network node i is defined as follows (Fagiolo, 2007):

$$dcc_i = \frac{\sum_{h \neq j}(a_{ij} + a_{ji})\,(a_{jh} + a_{hj})(a_{ih} + a_{hi})}{2(k_i(k_i - 1) - 2k_i^{\leftrightarrow})} \tag{8}$$

In the above formula, k_i is the sum of the node degrees i, which means that $k_i = k_i^{out} + k_i^{in}$ and $k_i^{\leftrightarrow} = \sum_j a_{ij}a_{ji}$ are the number of bidirectional edges.

4. Similarity measures

The cosine coefficient is most commonly used to measure the similarity of vectors. The cosine similarity is defined as follows:

$$\cos(\theta) = \frac{p.q}{\|p\|\|q\|} = \frac{\sum_{i=1}^{n} p_i q_i}{\sqrt{\sum_{i=1}^{n} p_i^2}\sqrt{\sum_{i=1}^{n} q_i^2}} \tag{9}$$

This coefficient is set to the interval of [-1, 1] (if the vectors are nonnegative this value will be in the interval [0, 1]. Here θ is the angle between p and q.

5. Measures of centrality

5.1. Degree centrality

One of the widely used centrality measures is the degree of centrality (Landherr, Friedl and Heidemann, 2010). The centrality of the node's degree is equal to the number of edges on that vertex. Suppose that G = (V, E) is an undirected graph with |V| as Vertex and |E| as Edge. Also, e = {v, u} denotes the undirected edge in graph G. The degree centraiity of that node is defined as follows:

$$C_{deg}(v) = \left|\left\{e \middle| e \in E \wedge v \in e = \{v, u\}\right\}\right| \quad (10)$$

In a directional network, there are usually two measures for the calculation of degree centrality based on the input and output conditions. If e = (v, u) denotes the direction of the vertex from v to u then we have:

$$C_{indeg}(v) = |\{e|e \in E \wedge e = (u, v)\}|$$

$$C_{outdeg}(v) = |\{e|e \in E \wedge e = (v, u)\}| \quad (11)$$

5.2. Betweenness centrality

The measure of intermediate centrality specifies the number of times a node acts as a connection through the shortest path between two nodes. C_B is the most appropriate centrality measure to determine the importance of a node and its effect on the overall graph connection (Kermarrec, 2011).

$$C_B(v_i) = \frac{1}{(n-1)(n-2)} \sum_{i \neq j \neq r \in V}^{N} \frac{k_{jr}(v_i)}{k_{jr}} \quad (12)$$

Where k_{jr} is the shortest number of paths from node v_j to node v_r in the network, $k_{jr}(v_i)$ is the number of shortest paths through nodes $v_i.C_B$ is one of the standard measures for node centrality, which was originally introduced to determine the importance of a node in a network (Boldi and Vigna, 2014). The higher the betweenness centrality of a vertex is the more the effect of that node on the system (Faghani and Nguyen, 2013; Liu, 2015).

5.3. Eigenvector centrality

Another centrality introduced by Bonacich (2007) is called eigenvector centricity. The basic idea of the eigenvector centrality is that the importance of a node is not only determined by itself but also influenced by the importance of its neighbors (Yu and Fun, 2015). In other words, by this measure the centrality of each vertex is directly related to the centrality of the adjacent vertices. So the higher centrality value of the neighbors of a node leads to higher centrality of that node. If x corresponds to the largest eigenvalue of matrix A, in other words,

$$Ax = \lambda_{\rho(A)}x \quad ; \quad \|x\| = 1 \tag{13}$$

Then the eigenvector centrality of vertex v_i at $V = \{v_1, v_2, \dots, v_n\}$ is equal to the element of the corresponding eigenvector of x (Landherr, Friedl and Heidemann, 2010; Kermarrec, 2011).

Data Analysis and Finding Results

In this section, we form a graph corresponding to each of the network layers including the layers of return, trading volume, and the value. The network corresponding to each layer is a weighted and directed graph. For this purpose and to determine the direction of the edges in each of the graphs, Granger causality test was applied and the weight of the edges was assigned based on the final prediction error (FPE). Charts 2, 3, and 4 represent the graph corresponding to the layers of return, volume and value, respectively.

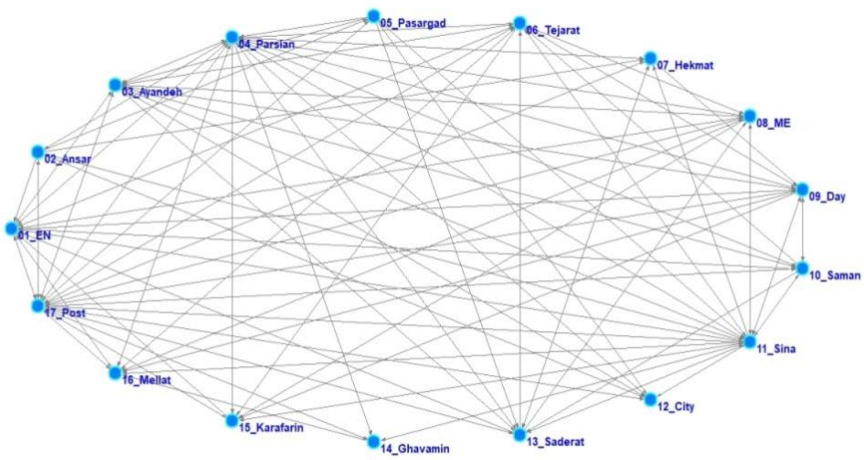

Figure 2. Graph corresponding to return layer

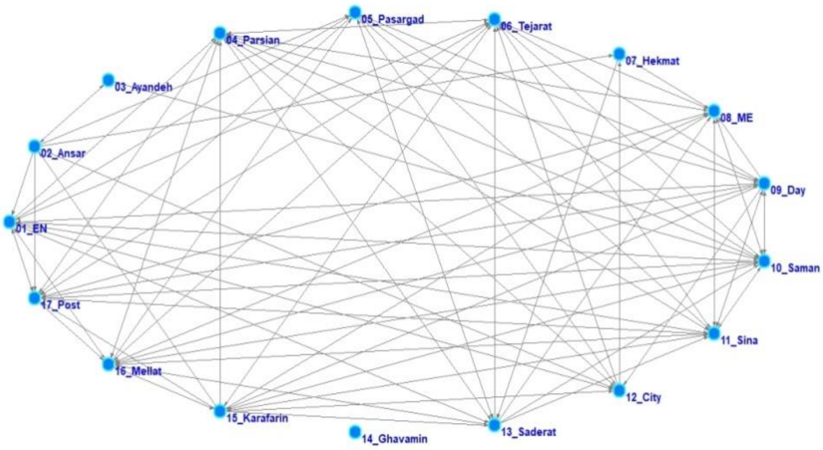

Figure 3. Graph corresponding to volume layer

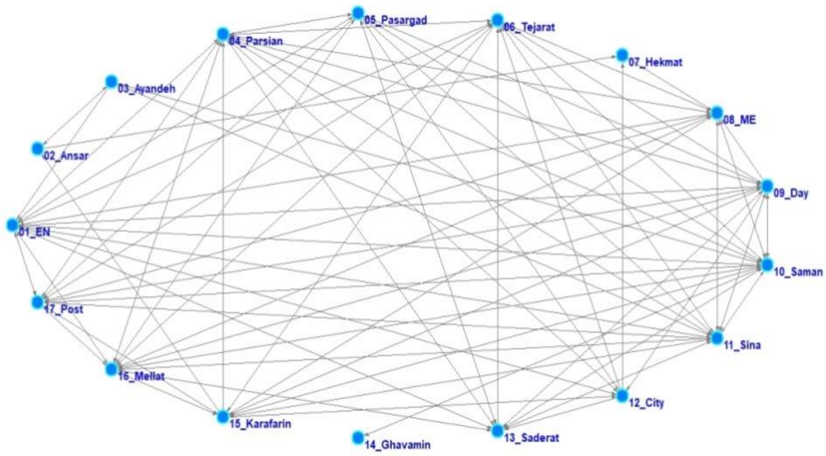

Figure 4. Graph corresponding to value layer

1. Network layer topology

In order to evaluate different layers of the network, we have computed some network metrics including density, reciprocity, node strength, and node clustering coefficients. We have examined all of these measures in each layer of the network. Table 1 shows the density and reciprocity in each layer of the network.

Table 1. Density and reciprocity measures in different network layers

	Return layer	Volume layer	Value layer
Reciprocity	0.369527	0.0482	0.094504
Density	0.430147	0.474265	0.525735

Figures 5 illustrates the strength of the various nodes of the network in different layers.

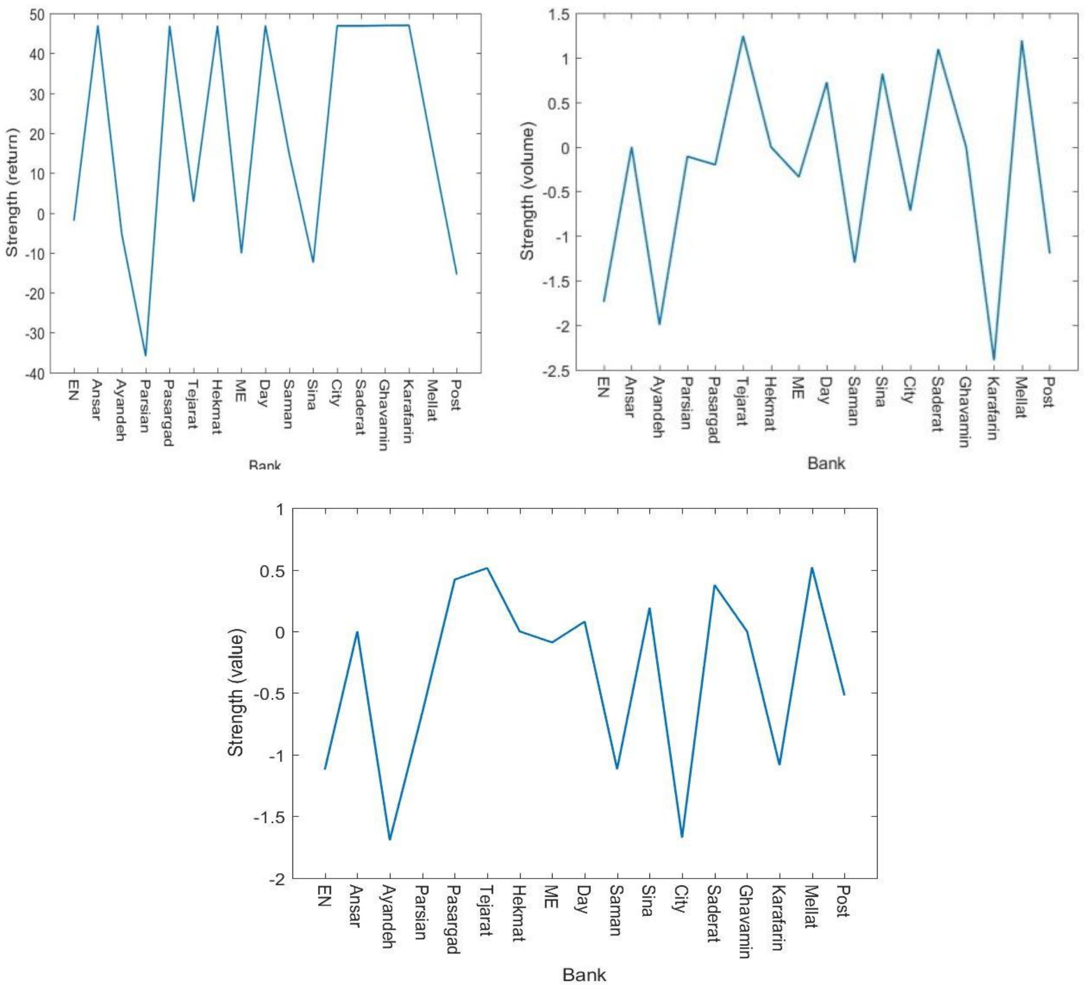

Figure 5. The strength of the nodes in the different layer

In Figures 6, the clustering coefficients of different network nodes in the layers of returns, trading volume and transaction value are presented.

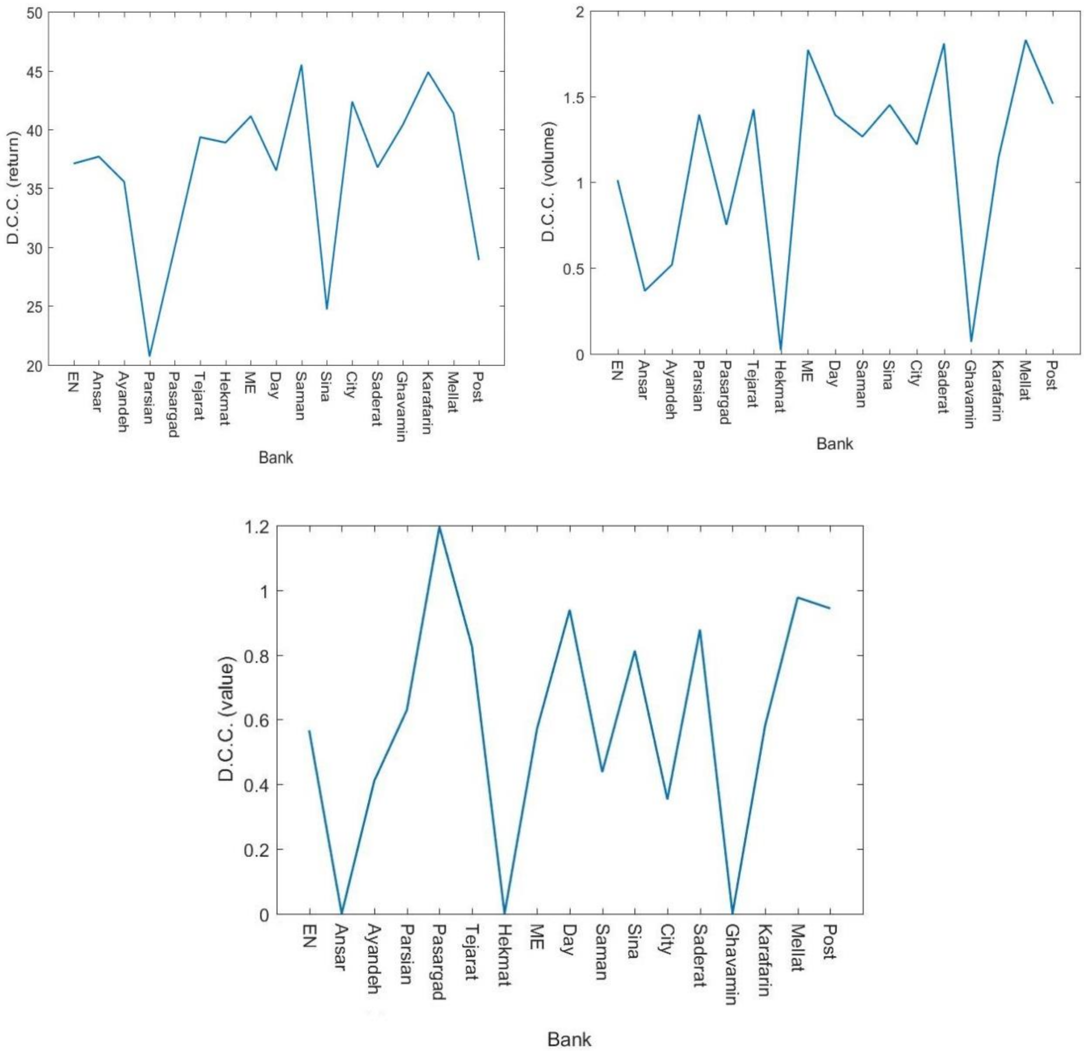

Figure 6.Clustering coefficients of nodes in different layer

2. Similarity of network layers

In this section, the similarity of the market value layer as a total layer to each of the returns and volume layers is investigated. For this purpose, the cosine similarity coefficient has been applied using the node strength vector and node clustering coefficients vector for different layers. The values obtained for the cosine similarity coefficient are presented in Table 2. Based on the values obtained, it is obvious that the market value layer is almost the same as the trading volume layer.

Table 2. Similarity of different layers to the value layer

	Cosin similarity (strength)	Cosin similarity (D. C. C.)
Similarity between value and return layer	%3.32	%-81.82
Similarity between value and volume layer	%94.22	%96.58

3. Centrality in network layers

In this section, the centrality of nodes in each layer is evaluated using degree, betweenness, and eigenvector centrality. Based on these measures the importance of the banks in each layer and how they behave in different layers has been evaluated. Tables 3, 4 and 5 show the centrality of each bank in terms of different layers. Also the rank of each bank is calculated according to the measures.

Table 3. Degree centrality in each layer

Bank	Return layer		Trading Volume layer		Value layer	
	Measure	Rank	Measure	rank	measure	Rank
E.N.	18	5	18	8	22	1
Ansar	4	17	6	15	5	16
Ayandeh	17	6	3	16	7	15
Parsian	27	1	21	3	23	3
Pasargad	8	12	10	13	12	12
Tejarat	18	4	20	4	21	7
Hekmat	7	14	3	17	4	17
M.E.	15	8	16	10	17	11
Day	15	7	20	5	22	5
Saman	14	9	27	1	27	1
Sina	25	2	20	6	22	6
City	5	15	12	12	12	13
Saderat	13	11	15	11	19	9
Ghavamin	4	16	9	14	10	14
Karafarin	7	13	17	9	18	10
Mellat	13	10	22	2	25	2
Post Bank	24	3	19	7	20	8

Table 4. Betweenness centrality in each layer

Bank	Return layer		Volume layer		Value layer	
	Measure	Rank	measure	rank	measure	Rank
E.N.	17	3	0	17	0	17
Ansar	0	17	14	6	3	10
Ayandeh	7	9	1	11	15	7
Parsian	3	11	0	16	0	16
Pasargad	15	6	28	4	17	5
Tejarat	11	8	46	1	25	3
Hekmat	0	16	26	5	0	15
M.E.	0	15	38	2	15	6
Day	15	5	0	15	0	14
Saman	5	10	13	7	27	2
Sina	16	4	0	14	24	4
City	0	14	12	9	11	9
Saderat	14	7	8	10	0	13
Ghavamin	0	13	0	13	0	12
Karafarin	0	12	12	8	12	8
Mellat	19	2	34	3	45	1
Post Bank	46	1	0	12	0	11

Table 5. Eigen vector centrality in each layer

Bank	Return layer		Volume layer		Value layer	
	Measure	Rank	measure	Rank	measure	Rank
E.N.	-0.2885	13	0.0404	10	0.0400	10
Ansar	-0.0043	2	0	15	0.0001	16
Ayandeh	-0.2801	12	0	16	0.0070	14
Parsian	-0.2251	8	0.0791	7	0.0579	9
Pasargad	-0.0796	6	0.1845	4	0.2825	4
Tejarat	-0.2744	11	0.6702	1	0.5017	2
Hekmat	-0.0468	5	0.0006	14	0.0000	17
M.E.	-0.2141	7	0.0493	9	0.0654	8
Day	-0.3236	15	0.1535	5	0.1259	6

Saman	-0.4308	17	0.0326	11	0.0376	12
Sina	-0.3101	14	0.1411	6	0.1280	5
City	0	1	0.016	13	0.0099	13
Saderat	-0.2329	9	0.3725	3	0.2879	3
Ghavamin	-0.0258	3	0	17	0.0003	15
Karafarin	-0.0335	4	0.0314	12	0.0379	11
Mellat	-0.2612	10	0.5631	2	0.7305	1
Post Bank	-0.3838	16	0.0699	8	0.0868	7

Conclusion

Multilayer network concept is the expansion of the network theory that can be used for better understanding the behavior of real markets.

In this paper, we have used this new concept to analyze the relationships between banks in Iranian capital market for three consecutive years. We have presented a three-layer network, with each layer corresponding to a specific network. The multiplex network is composed of the daily returns, trading volume and market values (named as the global layer) of the banking sector.

To investigate the topology of different layers of the network, we have used various measures, such as graph density, reciprocity, node strength, and clustering coefficients.

It is found that each layer has unique topological features, but the estimated densities of these layers are the same. The calculated reciprocity indicates that the difference between trading volume and value layers is less than the difference between the return and value layers in the terms of the corresponding graph edges.

After observing the strength values of the nodes in different layers of the network, we have found that the global layer (value layer) is very similar to the trading volume layer. The same result can be obtained by examining the values of clustering coefficients of nodes in different layers. To investigate the similarity of the global layer with the return and trading volume layers, the cosine similarity coefficient has been used. We have calculated this measure once by using the node strength vector and again by using the node clustering coefficients vector in different layers. The value of this coefficient in the case of the nodes strength indicates the high similarity of the global layer to the trading volume layer. This finding has been confirmed by using clustering coefficients. Finally, we have tried to define central nodes of the layers. For this purpose, we have used the measure of degree centrality, betweenness and eigenvector centrality. It is shown that there is a significant relationship between centrality of each bank in different layers.

Some medium-sized banks are central in some layers and peripheral in the other layers. Large banks such as Mellat Bank are in the core of all layers by different measures.This approach is useful for the policy makers to estimate the systemic risk and contagion in the financial sector.

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