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EVALUATION OF BORSA ISTANBUL WITH SOCIAL NETWORK ANALYSIS METHOD

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Abstract

Stock markets are one of the most important markets in the financial field. Evaluating stock data in these markets is important for investors to make decisions about portfolio diversity. At this decision point, visualizing the data and presenting it in a practical and interesting way provides great convenience to investors. Social network analysis is one of the methods used effectively in the visualization of data in a short time. The purpose of this study is to reveal the relations between stocks in Borsa Istanbul 100 (BIST 100) and also to identify the stocks that have a potential role and importance in BIST 100 with social network analysis method. The centralities of degree, betweenness and pagerank of stocks were established according to their degree of correlation. According to different threshold values, stocks that are effective, strong and popular were determined in the BIST 100. And also stocks were evaluated on sectorial basis. As a result of the study, it was observed that the sequence of the stocks with different threshold values changed according to the centrality metrics. Stocks in BIST 100 are interpreted according to each centrality criterion. All findings shows, BIST 100 is not under the influence of a limited number of stocks therefore BIST 100 does not have a fragile structure.

Keywords: BIST 100, Social Network Analysis, Stock Market, Borsa Istanbul

Jel Codes: C10, C88, G10, G15

1. Introduction

Today, with the advancement of technology, access to data has become easier and at the same time, causes complexity. Complexity is a scientific theory that claims, some systems exhibit behavioral phenomena that cannot be fully explained (Newman, 2010). The networks are composed of relations behind every complexity. Unless we can see and analyze these networks, it is not possible to understand complex systems such as the stock market. Relationships between stocks also emerge as a complexity.

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Investors who want to have high return rates, they should consider all environmental factors that affect stock prices and also follow the data for a long time and the past period with regularly. A lot of and complex data must be followed by investors. Therefore data must be transformed into easy-to-understand forms to enable investors to make decisions in a short time. One of the most important problems in finance is to find effective ways to summarize and visualize stock market data (Boginski, Butenko, and Pardalos 2006). Data visualization tools used in stock markets consist of traditional methods such as spreadsheets, graphs, etc., which are practical ways to present data in a meaningful way. However, these methods are not sufficient to reflect the relations between the stocks in the stock market. In addition, they do not have the sufficient skills to see the stocks positions, roles and effectiveness in the stock market. Network science can be used to overcome this problem. Network science provides users with many opportunities such as identifying groups, important nodes and connections, determining the roles and positions of nodes in the network. Moreover, network science has an undeniable importance in revealing tacit knowledge.

Revealing the relationships between stocks is important for investors to effectively manage their portfolios. Visualisation of stocks with graphs has high efficiency in enabling for investors to see the stock market and the relationships between stocks clearly at once. While graphical visualisation is often sufficient in the analysis of networks, numerical evaluations have also advantages on the analysis. In this study, both graphs and numerical values obtained from mathematical methods were used.

The purpose of this study is to reveal the relationships between stocks in BIST 100 and their roles in BIST 100 with social network analysis method. For this purpose, firstly the relevant literature was included in the study, then the method was introduced and the results were evaluated.

2. Literature Review

Social network analysis is frequently applied in many areas as a result of innovations that have emerged with the development of technology. When the studies on social network analysis in the literature are examined, it is applied in many scientific fields. Some of the studies conducted are briefly summarized as belows.

One of the studies on social network analysis in the field of health, belongs to Ariño and Torrent (2009). Ariño and Torrent (2009) tried to determine how professional and friendly relations in the health center personnel who are working in different fields in Spain. Iwashyna et al. (2009), investigated the movement of intensive care patients between hospitals with the method of social network analysis. As a result of study, they determined the differences in the health service provision of the hospitals at the regional level, the roles of the hospitals in the region and the improvements that could benefit the health system. Landim et al. (2010) examined the relationships between nurses in the hematology department of a hospital in Fortaleza using with social network analysis. Lee et al. (2011) investigated how some hospitals in California are related to each other in terms of patient referral with the method of social network analysis. Donker et al. (2012) revealed the spread of hospital infections with social network analysis. Iwashyna (2012) utilized social network analysis to review critical patient referral data between hospitals and identify barriers to the system in order to improve patient referral results. Ray et al. (2016) investigated the spread of Carbapenem infection which is highly resistant to antibiotics in patient transfers between hospitals with the method of social network analysis. An et al. (2017) evaluated the network of patients referred from one doctor to another in certain periods with social network analysis (Gönçer-Demiral, 2020).

Another area examined with social network analysis is bibliographic studies. Laing and Weiler (2008) examined the subjects on which postgraduate theses on tourism in Australia were written. Huang (2011) researched the areas in which doctoral dissertations are studied with social network analysis. Al et al. (2012) examined the publications from the year (1968) the first publication entered the citation indexes of Hacettepe University until 2009 in terms of various bibliometric features and evaluated the obtained data using the social network analysis method. Karagöz and Yüncü (2013) examined the research topics discussed in the doctoral thesis produced in Turkey between 1991-2010 with social network analysis and revealed the tourism information network structure and evaluated its transformation over the years. Özkan and Alp (2016) examined the research topics of the articles published in the journals scanned in the 2015 Science Direct electronic database and the operations research knowledge network structure between the countries of the universities where the authors worked with social network analysis.

Social network analysis studies, which are dealt with in the economic framework in the literature, take a very large place. Cetorelli and Peristiani (2009) evaluated the relative importance of financial centers around the world using social network analysis. Toomet et al. (2012) analyzed the relationships between unexplained racial/ethnic wage differences using social network analysis. Argan (2014) demonstrated the development of a complaint map between consumers in terms of mobile phone brands in Turkey by a customer complaints website. The results of the research revealed that product replacement, warranty, operating system, battery life, speaker, signal and product return are important connection points in terms of consumer complaints. Otamış and Yüzbaşıoğlu (2015) aimed to measure the global cooperation and innovative performance and growth trend of hospitals in the international medical tourism sector in Antalya, using the social network analysis approach. Dimitrios and Vasileios (2015) analyzed the stock relations in the Greek stock market between 2007 and 2012 using network analysis. Walther (2015) utilized social network analysis to understand the informal trade of African countries. Baykal and Gürbüz (2016) investigated social capital using social network analysis based on the results of their survey data conducted at a company operating in the defense industry in Turkey. Tang et al. (2018) made an in-depth analysis of the stock markets of China (CSI300) and the United States (S

& P 500), two of the most influential economies, through social network analysis using the daily closing prices. Hua et al. (2019) applied social network analysis with measurements of betweenness, closeness, eigenvector, PageRank and weighted degree of centrality using the data of 5,088 stocks in the Australian stock market. Alkan (2019) evaluated by whom credit and commercial transactions were carried out more widely in Istanbul in the 17th century within the framework of a classification based on belief, using the social network analysis. Yakıcı-Ayan and Değirmenci (2020) investigated the connections between world stock markets by using the social network analysis method with the stock closing values of 2018.

3. Method

In this research, the relationship of BIST 100 stocks for 2018 and their rankings according to their centrality values were evaluated by the social network analysis method.

In the study, Pearson's linear correlation coefficients were used as correlation criteria in determining the relationships between indices. Symmetric matrices of 100x100 were created separately for different threshold values (θ) between 0.1 and 0.9. Undirected networks were obtained by transferring the correlation matrices to Nodexl which is one of the social network analysis software. The connection between the two stocks represents positive and negative behavior between stocks. In the positive correlation coefficient, stock prices move in the same direction while, in the negative correlation coefficient, they move in opposite directions. In this study, only stocks with positive correlations were taken into consideration. Networks were formed according to all values in the correlation matrix; some of them were graphically represented due to space constraints.

A network consists of nodes and connections between nodes. In the study, each stock represents a node, and the connections between stocks represent the edge. “Relationship” or “connection” words are used instead of edges to increase clarity.

Network statistics and node statistics are used to understand the structures of networks and see their changes in the process. While network statistics make evaluations for the whole network, node statistics are interpreted with centrality metrics. In the study, firstly, whole network properties were evaluated according to all correlation values and then centrality criterias were evaluated. In the whole network metric, the number of nodes and connections, density, and diameter properties of the network were dealed.

With the centrality metrics, all nodes receive numerical values and these values allow comparison of them with other nodes in the network. In this way, the location, importance, influence and popularity of nodes in the network can be determined. Centrality metrics are the most important criterias used in network analysis, and each criterion provides different interpretations on nodes. Among these criteria are degree, betweenness, closeness, eigenvector, and PageRank centralities. In the study, metrics are used to determine the relative importance of each stock in the network. They are very useful and important as it can give a general idea to the stakeholders about the future investments. A node in the network may be important and effective by one of the centrality metric, but not by another. For this reason, different metrics are taken into account in network analysis rather than a single metric. Degree, betweenness, and pagerank centrality metrics were used and interpreted in this study.

4. Results

Graphs were created for different threshold values starting from 0.1 up to 0.9. The network metrics are shown in Table 1. Up to a threshold value of 0.6, the number of nodes of the network was constant (100), and the number of nodes started to decrease after the threshold value of 0.7. As the threshold value increases, the number of connections decrease and thus the density begins to decrease. The density of a graph is calculated by dividing the number of connections available in the network by the total number of connections that should be available. A density value of 1 means that the nodes in the network are completely interconnected, which is called a *complete graph.* In high-density networks, cooperation between nodes is high and information flow between nodes is fast. However, high-density networks exhibit the property of closure. In other words, the flow of resources and information from outside to the network is limited and slow (Öztaş and Acar 2004). Therefore, high-density networks are also considered structures in which innovative and creative ideas, new resources and alliances are restricted. The density of the network with a threshold value of 0.1 is 0.91, indicating that the connection of stocks with each other is 91% and that the cooperation and information flow is high. At the threshold value of 0.1, the density of the network is the highest and at the closest value to the complete graph. It is seen that the density of the network decreases to 0.32 in parallel with the number of connections at the threshold value of 0.9. This means that the connection between the stocks in the network is 32%.

The increase in diameter length as the threshold value indicates that there is a clustering in the network by the certain stocks are in connection with certain stocks. The disconnection of some stocks in the network can also cause the diameter length to increase. This is also evident from the increase in the number of isolated nodes according to the correlation threshold values.Nodes with zero degrees in the network are called isolated nodes. These nodes are in an inactive position in the network. According to Table 1, the number of *isolated nodes* increases as the threshold value increases. The number of nodes, which was 100 at the beginning, decreased to 56 when the threshold value reached 0.9. This situation gives the information that nodes with a threshold value of 0.9 are core and strong stocks in the stock market.

The nodes with the highest degree change according to the threshold value. GOZDE is the stock with the highest degree according to the threshold value of 0.1 and 0.9. It can be said that the GOZDE stock has a very important position in positive threshold values and played a determining role in the prices of other stocks.

The node with the lowest degree is the IPEKE stock. After the threshold of 0.7, the IPEKE stock moved out of the network, as it was an isolated node.

Table 1. Network Metrics According to Positive Threshold

Threshold Value	Number of Nodes	Number of Connections	Density	Diameter	Max degree	Stocks with a Max Degree	Min Degree	Stocks with a Minimum Degree	Number of Isolated Nodes
0.1	100	4499	0.91	2	97	GOZDE ECILC HALKB TCELL	50	IPEKE	-
0.2	100	4063	0.82	2	95	TOASO	24	IPEKE	-
0.3	100	3610	0.73	2	88	AGHOL GUBRF ODAS	12	IPEKE-MPARK	-
0.4	100	3162	0.64	3	83	AFYON ULKER	2	IPEKE	-
0.5	100	2662	0.54	5	76	GOZDE AGHOL ODAŞ TTRAK	1	IPEKE	-
0.6	100	2176	0.44	6	68	TAOSO	1	SASA KOZAA IPEKE THYAO PARSN	-
0.7	95	1679	0.38	8	61	GOLTS GUBRF ULKER	1	VERUS OZGYO SASA KOZAA IPEKE IEYHO FROTO ENKAI ISFIN ICBCT PARSN	5
0.8	73	1188	0.45	7	52	TSKB	1	BIMAS EGEEN ENJSA EREGL KCHOL KRDMD MPARK VERUS	27
0.9	56	495	0.32	6	35	GOZDE DGKLB GOLTS	1	ASELS CLEBI ENJSA MPARK TKFEN	44

Table 2 shows the sectors of the 100 stocks of the BIST 100. All stocks include a total of 10 different sectors.

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Table 2. Distribution of Stocks by Sectors

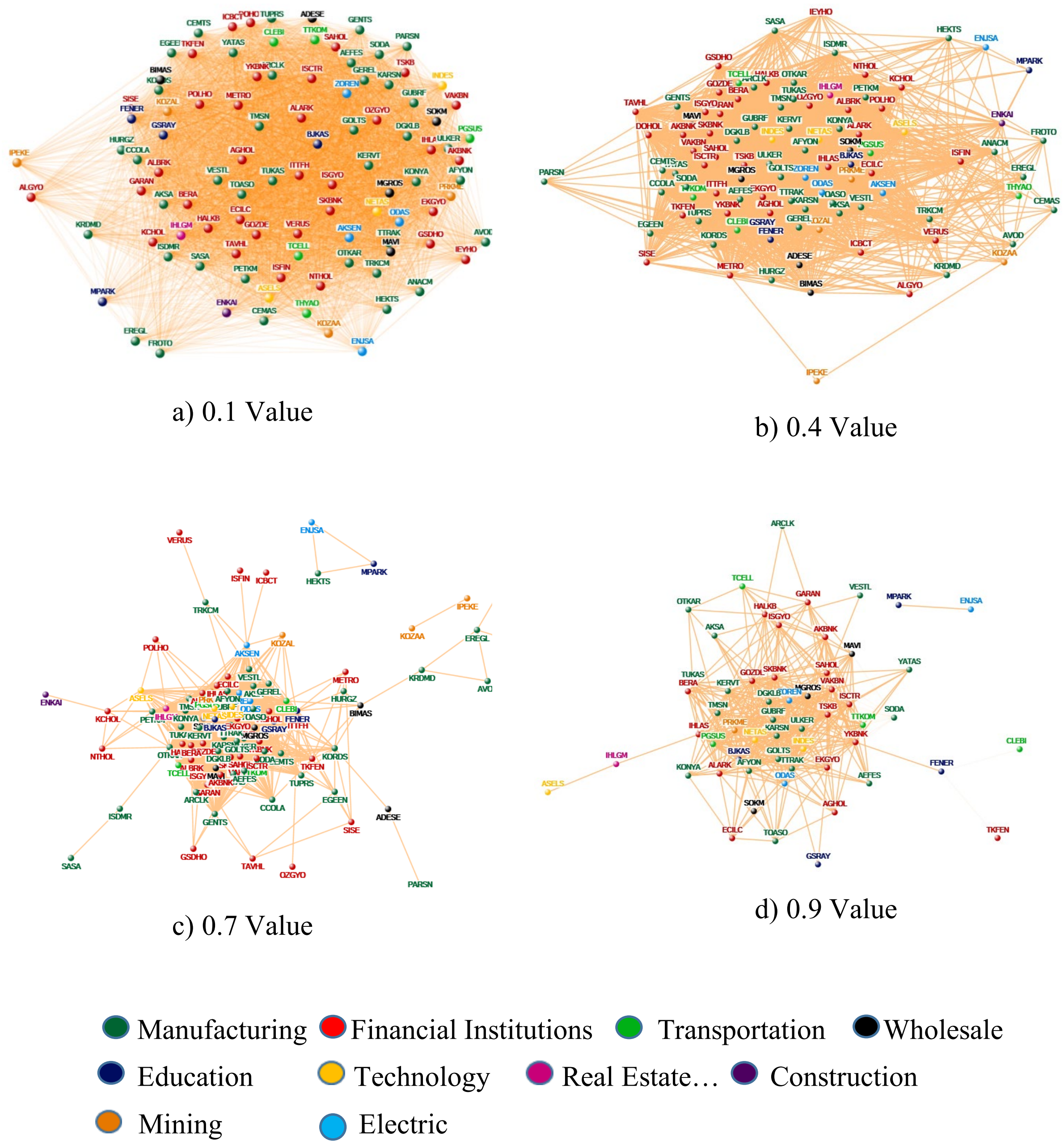
Sectors	**Number of Stocks**
Manufacturing	39
Financial Institutions	34
Transportation, Storage And Communication	5
Wholesale and Retail Trade, Restaurants and Hotels	5
Education, Health, Sports and Other Social Services	4
Electric, Gas and Water	4
Mining and Quarrying	4
Technology	3
Real Estate Operations	1
Construction and Public Works	1
Total	100

Graphs provide time savings and clarity in data visualizations. The representation of the graphs for different threshold values (0.1, 0.4, 0.7, and 0.9) using the Harel-Koren algorithm in the NodeXL software is shown in Figure 1. Each node is colored sectorally. As can be seen from the graphs, threshold values getting greater, network complexity is decreasing. According to the algorithm, nodes with more connections are located in the middle of the graph, and nodes with fewer connections are located at the edges of the graph. The nodes on the far edges of the graph are with the lowest degree stocks (Example: θ-0.1 IPEKE, θ-0.4 PARSN, θ-0.7 FROTO, θ-0.9 ASELS).

Graphs can be divided into a certain number of sub-graphs. Such sub-graphs are called *components*. When there are no isolated nodes in the graphs and there are no subcomponents of the graphs, the network alone is a giant structure. The component structures of stock networks have great implications for the risk management of a portfolio. Investing in stocks from different components instead of investing in multiple stocks within the same component will diversify and reduce the risk (Tang et al.2018). It is seen that as the threshold value increases, the components are formed. In figure 1c and 1d, the ENJSA, HEKS, MPARK and KOZAA, IPEKE stocks, and MPARK and ENJSA stocks are positioned separately from the graph and are a component each with respectively. It is understood from the graphs that an investor should not invest in both KOZAA and IPEKE stocks. In this sense, distinguishing the components within the networks is of great importance.

Stocks in the education, health, sports and other social services, technology and real estate sectors are fully included in the graphs at all threshold values. Despite this, some of the stocks that belong to other sectors appear to have moved out of the network. Although the number of nodes is small, it can be thought that stocks in the field of education, technology, and real estate can be evaluated by investors.

Figure 1. BIST 100 Index Graphs by Threshold Values



a) 0.1 Value

b) 0.4 Value

c) 0.7 Value

d) 0.9 Value

Centrality Metrics

Table 3 shows the centrality metrics used in the study according to the threshold value 0.1 in the portfolio of BIST 100 stocks. Due to space restrictions, stocks in the top 10 and bottom 10 are shown.

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Table 3. BIST 100 Index Centrality Values by Threshold Value of 0.1

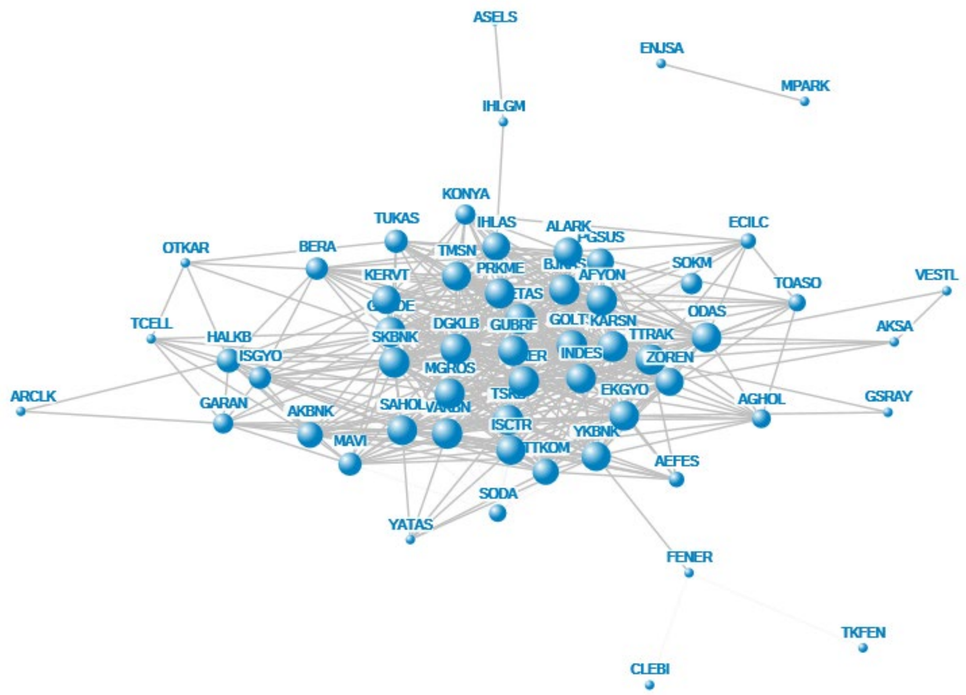
Rank	Degree Centrality		Betweenness Centrality		Pagerank Centrality	
1	TCELL	97	IHLGM	6.4997	TCELL	1.0672
2	ECILC	97	ISFIN	6.4648	ECILC	1.0671
3	HALKB	97	METRO	6.4177	HALKB	1.0669
4	GOZDE	97	BIMAS	6.2395	GOZDE	1.0669
5	IHLGM	96	PETKM	6.2283	IHLGM	1.0586
6	OTKAR	96	TAVHL	6.1273	OTKAR	1.0578
7	AGHOL	96	KCHOL	6.0950	AGHOL	1.0575
8	BERA	96	HURGZ	6.0616	BERA	1.0573
9	ALARK	96	SASA	5.9962	ALARK	1.0571
10	TOASO	96	CCOLA	5.9849	TOASO	1.0569
.	.	.	.	.	.	
.	.	.	.	.	.	
.	.	.	.	.	.	
91	IEYHO	80	KARSN	3.13419	IEYHO	0.9061
92	KOZAA	77	SODA	3.12026	KOZAA	0.8782
93	KRDMD	75	PGSUS	3.03455	KRDMD	0.8601
94	AVOD	73	YATAS	3.03408	AVOD	0.8409
95	ENJSA	69	FROTO	2.97838	ENJSA	0.8028
96	MPARK	63	TSKB	2.90651	MPARK	0.7473
97	ALGYO	62	EREGL	2.78622	ALGYO	0.7379
98	EREGL	60	VAKBN	2.68344	EREGL	0.7189
99	FROTO	58	INDES	2.57977	FROTO	0.7007
100	IPEKE	50	IPEKE	2.47668	IPEKE	0.6246

Degree Centrality

The degree of a node is the number of neighbors to which it is attached. Each node in the network can have a different number of connections. Degree centrality is the most commonly used simple measure of centrality that determines the importance of nodes in the network. In an undirected network, the degree of a node is equivalent to the total number of connections available on that node. The degree of centrality value of a stock used in the study refers to the number of connections with the other stocks in the stock market. High-degree stocks directly affect the behavior of the stocks that depend on them. Accordingly, TCELL, ECILC, HALKB stocks with the highest degree according to Table 3 affect many stocks in the BIST 100. IPEKE is the stock with the lowest degree and is always influenced by with nodes which is higher degree than itself. IPEKE is the stock with the lowest degree for all threshold values.

According to the threshold value of 0.9, its degree centrality graph is shown in Figure 2. The size of the nodes also refers to the height of the degree. Nodes with a small degree appear to be positioned towards the edges of the graph. Accordingly, it seems that some stocks with a high degree of threshold value 0.1 (eg. TCELL, ECILC) were rated lower on the network compared to the threshold value of 0.9. A large number of nodes with a high degree indicate that the network is more resilient to any targeted attacks from outside. Because in a targeted attack on a particular stock (e.g. speculative behavior) since there are multiple nodes with a high degree within the network, others are not affected by this attack and the network does not crash.

Figure 2. BIST 100 Degree Centrality Graph According To The Threshold Value of 09



Betweenness Centrality

Betweenness centrality is defined as the number of shortest paths between node pairs. It indicates the extent to which a node is connected with non-directly connected nodes. Calculating the betweenness centrality, defined as the number of shortest paths between node pairs, is one of the most complex metrics. It deals with where the node is located on the network, rather than the number of nodes connected. The node with a high betweenness centrality controls the flow of information between other nodes. Thus, it has a significant effect on the network. The stock, which has a high betweenness centrality, has a significant impact in terms of controlling and coordinating the flow of information among other stocks. According to Table 3, the IHLGM (6.3997) stock has the highest value of betweenness. It indicates that the stock is in the best position within 100 stocks and that any positive or negative information passing through IHLGM is effective within BIST 100.

Figure 3 shows the centrality of stocks by the threshold value of 0.9. A change in the node color from light to dark means that the betweenness centrality value also getting high. Accordingly, YKBNK stock is the one with the highest betweenness value among all stocks. The FENER stock has the highest value in the education, health, sports, and other social services sectors. It is seen that stocks that have a high

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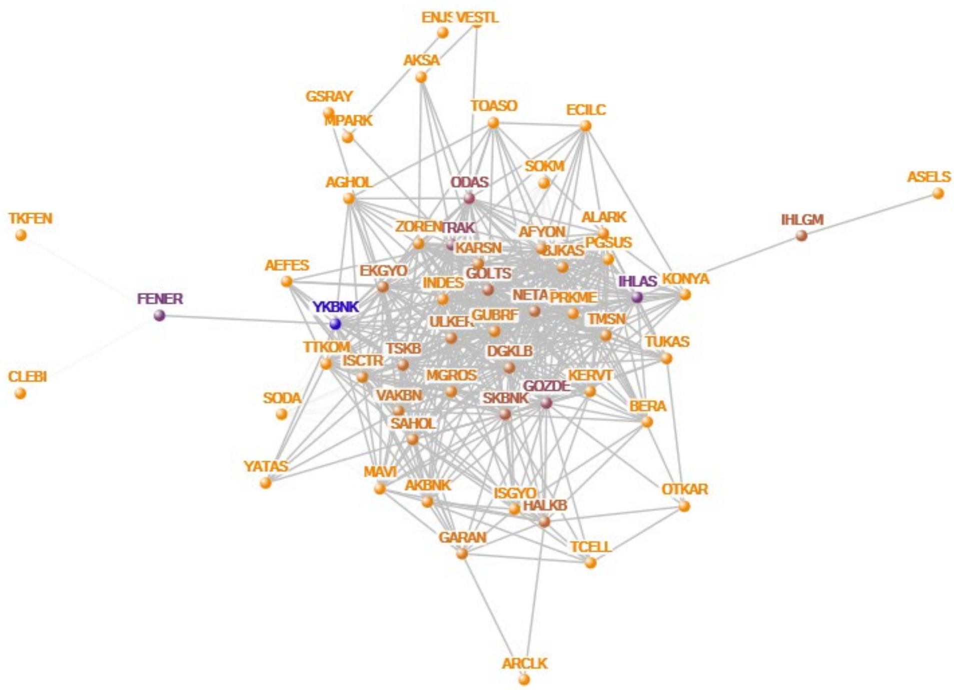
value of betweenness according to the threshold value of 0.1 do not exist at the threshold value of 0.9. This result is also an expression that different nodes can be included in the centrality metrics according to the threshold values.

Figure 3. Betweenness Centrality Graph of BIST 100 According to the Threshold Value of 0.9



PageRank Centrality

Not all nodes within a network have the same degree or the same importance. Most often, connecting to a node with a large number of connections within the network is more effective than connecting to a node with less or non connection. The importance of a node within the network depends on the importance of neighbors in the network, rather than the number of neighbors to which it is connected (Newman 2010). A node that is connected to a small number of but important nodes have a high eigenvector centrality (Bonacich 2007). The eigenvector centrality is indicative of the power and status of a node. Such central nodes, taking advantage of their power (prestige) are in a privileged position to monitor and control resources and information within the network (Gönçer-Demiral 2020). The Pagerank algorithm used by Google's search engine is a variant of eigenvector centrality (Hansen, Shneiderman, and Smith 2011). First used to sort web pages in web search engine design, Pagerank is quite effective for measuring the importance of nodes. Nodes with a high PageRank centrality degree are nodes that are popular in the network. The effect of nodes on the network can be evaluated by PageRank centrality (Chen, Zheng, and Zeng 2020). According to Table 3, TCELL (1.0672) is the most popular and prestigious node in the stock portfolio with the highest value. The stock with the lowest value is, again, IPEKE (0.6246).

Figure 4 shows the PageRank centrality graph by the threshold value of 0.9. The visibility of nodes in the graph varies according to their PageRank values. Accordingly, those with a high PageRank value are more pronounced and others are paler in color. It is observed that there are multiple stocks with a high value on the graph. Those with a PageRank value below average are shown as rhombuses. Stocks in dark colors such as TTRAK, GOZDE, GOLTS, DGKLB are the most prestigious and popular stocks in the network.

Figure 4. BIST 100 Index PageRank Centrality Graph According to the Threshold Value of 0.9

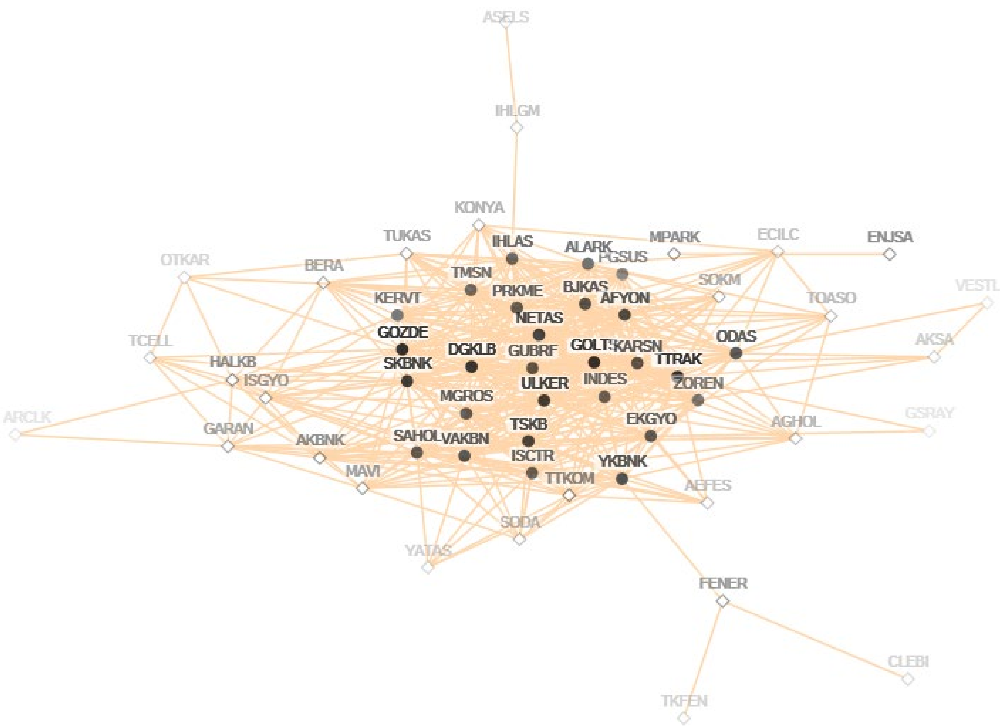


Table 4 shows the average degree, betweenness, and PageRank centrality of the stocks in the BIST 100 Index by the threshold value of 0.1. According to average degree values, the Real Estate Sector has the highest value (96), the Mining and Quarrying Sector has the lowest value (79) and other sectors are approximately close to each other. The Real Estate Sector also has the highest values in average betweenness (6.5) and PageRank values (1.059). It means that the real estate sector plays a decisive role in the BIST 100 stock market and the Mining Sector has the least impact. According to the average PageRank value, the Technology Field (1.025) seems to be the most popular sector following the Real Estate Sector. According to average betweenness values, the sectors that affect BIST 100 stock market the most are Real Estate (6.50), Construction and Public works (4.971) and Financial Institutions (4.667).

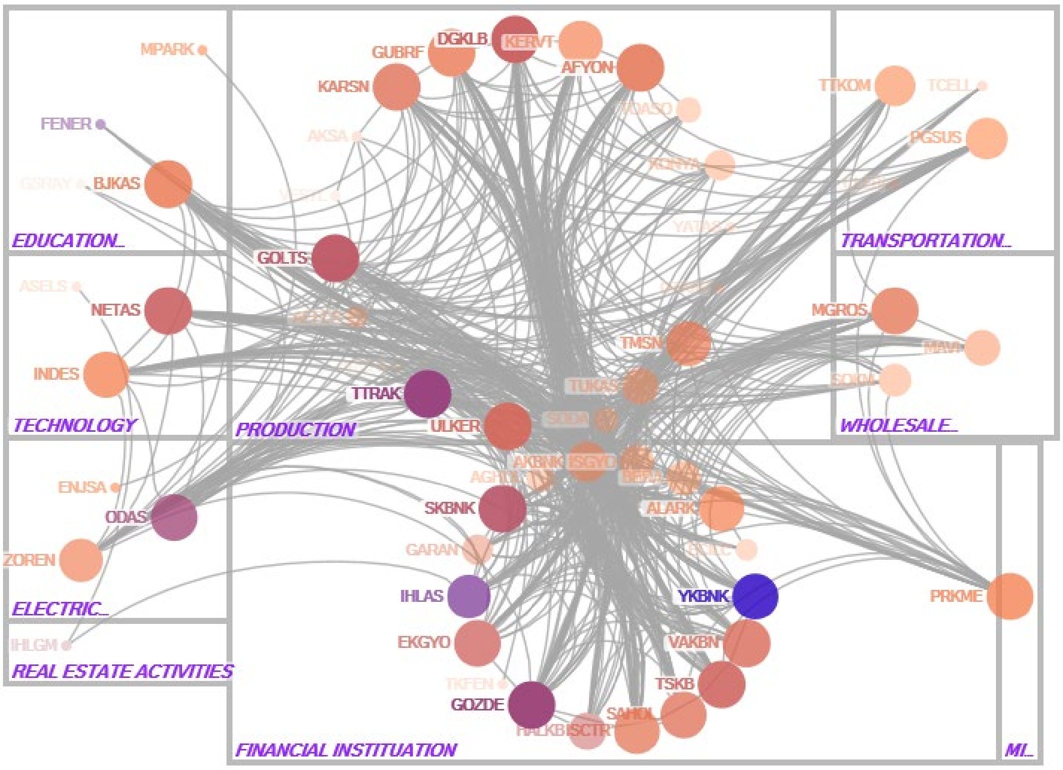
Table 4. BIST 100 Index Sectorial Assessment According The Threshold Value of 0.1

SECTORS	Number of Nodes	Average Degree	Average Betweenness	Average Pagerank
PRODUCTION	39	89	4,458	0,993
FINANCIAL INSTITUTIONS	34	92	4,667	1,020
WHOLESALE AND RETAIL TRADE, RESTAURANTS AND HOTELS	5	92	4,611	1,019
TRANSPORTATION, STORAGE AND COMMUNICATION	5	92	4,427	1,017
ELECTRIC, GAS AND WATER	4	88	4,170	0,981
MINING AND QUARRYING	4	79	3,724	0,894
EDUCATION, HEALTH, SPORTS AND OTHER SOCIAL SERVICES	4	86	4,365	0,963
TECHNOLOGY	3	93	4,266	1,025
REAL ESTATE ACTIVITIES	1	96	6,500	1,059
CONSTRUCTION AND PUBLIC WORKS	1	83	4,971	0,936

Figure 5 shows the relationship of the sectors with each other by the threshold value of 0.9. In the graph, it is observed that the sectors highly interact with each other as seen from the connections between them. According to the graph, the sizes of the nodes refer to their degree; the nodes from light to dark colors refer to the betweenness centrality values, and the opacity of the nodes refers to the PageRank values.

It is seen that the Construction Sector is not included in the network at this threshold value. Among other sectors, at least one stock has a high degree. BJKAS in Education, Health, Sports, and Other Social Services; INDES and NETAS in Technology; ZOREN and ODAS in Electronics; MIGROS in Wholesale and Retail, PGSUS and TTKOM in Transportation, and PPKME in Mining Sectors are the stocks with a high degree. It is understood from the graph that the stocks in the Financial Institutions Sector have not only a high degree value but also high betweenness and PageRank values. According to the threshold value of 0.9, this means that the Financial Institutions Sector is strong, effective and popular in the BIST 100 and investment can be made in stocks in this area. According to the threshold value of 0.1, the Real Estate Sector is considered as one of the areas that should be invested because its impact at the threshold value of 0.9 is quite low. The fact that TTRAK, GOZDE, GOLTS stocks are more prominently included in the graph indicates that they are popular and prestigious investments.

Figure 5. BIST 100 Index Sectors Graph According To The Threshold Value of 0.9



5. Conclusion

In this study, the analysis of stocks that have a positive relationship with each other in the BIST 100 Index was evaluated using with the social network analysis method. Networks were created for threshold values from 0.1 to 0.9. The fact that the degrees of the stocks in the BIST 100 are close to each other and in large numbers indicates that the BIST 100 index is resilient to any external economic attack. The BIST 100 Index is not under the influence of a single stock therefore providing dynamism with multiple stocks. This is an indication that BIST 100 market is not fragile.

Analysis of stock markets is necessary for investors and is also important in reaching summary information in a short time. Social network analysis is one of the most effective ways to visually show the relationships between stocks, as well as numerical evaluations, to demonstration at once stocks that are effective, strong and popular in the market. This is how network analyses can improve the decision-making skills of investors. This study shows that for investors, network analysis techniques are used effectively in stock markets; hopes to inspire wider applications for researchers.

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