

A Network Analysis Of The Pakistan Stock Exchange

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Abstract

The study uses network theory to develop, visualize and understand the stock network structures in the Pakistan Stock Exchange (PSX). An important contribution of this research is that it is the first study to use the centrality metrics and node strength to understand the stock network structures in the PSX. In this paper stock returns and stock return volatilities are used to develop the stock networks which is another contribution of the study. The highest market capitalization stocks listed on the KSE 100 Index of the PSX are studied from the year 2000 to 2018. The networks for each year were constructed and filtered using the Bonferroni Correction. Network centralities for each stock were estimated using both stock returns and stock return volatilities. The results show that stock returns volatility is a better measure for developing similarity-based networks, such as the stock networks, as compared to stock returns. It is also inferred that the PSX is influenced by a few major stocks.

Keywords: Network theory; Stock returns; Stock returns volatility; Network centrality; Node strength; Pakistan Stock Exchange.

Declarations

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1. Introduction

Today's global financial system is an extremely interconnected network in which the different financial institutions and individual investors are connected to each other through complex network structures, such as, stock investments, interbank payments and board memberships (Hu, Schwabe & Li, 2015). Among these complex network structures, the stock market has become an important subject of the economy where companies raise funds by issuing stocks and investors try to find arbitrage opportunities (Sharif & Djauhari, 2012). The stock market has captured the attention of not only the conventional players but also of researchers from diverse fields of study such as, physics and mathematics (Lee & Djauhari, 2012).

Among the various areas' researchers are using network theory to study the stock markets around the globe. Analysts have used the tools and techniques from network theory to explore the nature of stock networks to forecast stock returns in stock markets. Stock markets are one of the most complex financial networks being studied in the theory of finance due to the large amount of available data. A financial network is a graph, where a graph is composed of a set of "nodes" which are connected by links known as "edges." A stock network structure is a graph, where nodes are stocks and edges/links are developed based on the correlations among the stocks (Soramaki & Cook, 2016).

Research studies on the stock markets of United States of America, Brazil, India, China, Greece, Iran and South Korea that have applied the techniques of Network Theory provide useful insights in this regard. These studies conclude that the stock markets of the countries are scale-free networks, where a few stocks influence the entire stock market (Dimitrios & Vasileios, 2015; Namaki, Shirazi, Raei & Jafari, 2011; Tse, Liu & Lau, 2010; Huang, Zhuang & Yao, 2009; Tabak, Takami, Cajueiro & Petitinga, 2009).

Therefore, the application of network theory on the Pakistan Stock Exchange (PSX) will be the most important contribution of this study as there are no known studies in the literature to have conducted a similar study. Two types of networks are generated for each year from 2000 to 2018 using stock returns and stock return volatilities. The most important relationships in the networks are extracted using statistical significance testing. Then, network centralities are estimated for the two types of networks to find out the most important stocks in the networks.

2. Literature Review

2.1 Network Theory

An area of study that has received much attention now-a-days is the field of network theory. The subject of network theory is quite new and linked to Graph Theory. The roots of graph theory are attributed to the famously known problem, "The Seven Bridges of Königsberg," in 1735 in the city of Königsberg, Prussia (now Kaliningrad, Russia) which was studied by the famous mathematician Leonhard Euler by considering land masses as nodes and bridges as edges (Euler, 1741).

However, the word graph was first used by an English Mathematician James J. Sylvester in his paper "Chemistry and Algebra" in the context of natural sciences in the year

1878, in which he wrote, “Every invariant and covariant thus becomes expressible by a graph precisely identical with a Kekulean diagram or chemicograph” (Estrada, 2014). In the year 1889, the British Mathematician Cayley used graph theory to study graphs, that is, tree, which led to the Cayley-trees where each node has an identical number of connections (Cayley, 1889).

It is important to note that the terms graph and network have been used indistinctly in literature (Estrada, 2014). According to Rodrigue & Ducruet (2017) a graph can be defined as, “A symbolic representation of a network and its connectivity.” A graph represents an abstraction of reality so that it can be simplified as a set of linked nodes.

There exists a wide and specific vocabulary that describes different kinds of graphs with distinct internal structures, subgraphs, and individual nodes with mutual links. Graphs can be visualized through matrices or by the node/link view and graph theory depends on a specific vocabulary to describe networks where, nodes are labelled as vertices (vertex) and links are labelled as edges, respectively (Rodrigue & Ducruet, 2017).

2.1.1 Fundamental Elements of Graph Theory

According to Rodrigue & Ducruet (2017) the following are few of the fundamental elements that would help in understanding the graph theory:

- Graph: “A graph G is a set of vertices (nodes) v connected by edges (links) e . Thus, $G = (v, e)$.”
- Vertex (Node): “A node v is an intersection point or terminal point in a graph. It is the abstraction of a location such as a city, an administrative division, a road intersection or a transport terminal.”
- Edge (Link): “An edge e is a link between two nodes. A link is the abstraction of a transport infrastructure supporting movements between nodes. It has a direction that is commonly represented as an arrow. When an arrow is not used, it is assumed the link is bi-directional.”

Many researchers around the world are using graph theory in different disciplines. It has notably inspired the field of network theory (Derrible & Kennedy, 2011).

A study on the network structure of various industries of the Chinese Stock Market indicated that a relationship exists between stock centrality and stock returns (Chen, Luo, Sun, & Wang, 2015). A comparative analysis of the network structures of the Dow Jones Industrial Average and the Tehran Stock Exchange using the market mode technique and the threshold method showed that the networks follow a power-law model (Namaki, Shirazi, Raei, & Jafari, 2011). Complex networks for the closing prices of all the US stocks were studied during two time periods, July 2005-August 2007, and June 2007-May 2009. The results reported that the networks of the US stocks show a scale-free distribution where the changes in stocks prices are greatly affected by a very small number of stocks (Tse, Liu, & Lau, 2010).

Most of the literature on the stock network structures focuses on exploring the correlations that exist among the stocks. The Chinese stock market of the financial industry was studied by obtaining the correlation coefficients using the correlation coefficient formula and the networks were constructed using the threshold method. Centrality analysis was performed with degree, closeness and betweenness centrality, and the small-world network characteristics of the stock network of the financial industry were reported (Nie, Zhang, Chen,

& Lv, 2015). The market graph models were constructed for different time periods from 2007-2011 for studying the Russian Stock Market. The results showed a strong relation between the volume of stocks and the structure of maximum cliques also, stocks have a strong correlation between their returns (Vizgunov, et al., 2014). The Brazilian stock market networks were studied using the minimum spanning trees based on ultrametricity and a dynamic approach using complex measures. The study concluded that the Brazilian stocks tend to cluster by sector and the importance of various sectors within the network varies (Tabak, Serra, & Cajueiro, 2010). The Korean stock market network structure was constructed with minimum spanning trees. It was found that the Korean stock market is characteristically different from the mature markets as it does not form the clusters of the business sectors as compared to when the Morgan Stanley Capital International Inc. (MSCI) is exploited where clusters of the Korean stock market are found (Jung, Chae, Yang, & Moon, 2006).

2.2 The Network Structures

“Network structures are graphs with properties, where a graph is a set of nodes, pairs of which may be joined by links and stock network structures are similarity-based networks, where a common similarity measure is the correlation between each pair of nodes” (Soramaki & Cook, 2016, p. 7, 24).

Centrality is basically a measure of how a network’s structure contributes to a node’s importance. Among others, there are three fundamental measures of centrality, degree, closeness and betweenness (Dimitrios & Vasileios, 2015; Lee & Djauhari, 2012). Degree centrality is the simplest measure of centrality measuring the number of direct ties incident upon a node, closeness centrality is the inverse of the average geodesic distance between a node i and all other nodes, where geodesic distance is the shortest distance or the length of the geodesic path among the nodes and betweenness centrality measures the extent to which a node lies on the shortest path between pairs of other nodes (Badar, Hite, & Badir, 2013; Freeman, 1977). Node strength is the sum of all the correlation coefficients of a node i with all the other nodes in the network (Huang, Zhuang, Yao, & Ursayev, 2016; Wang & Xie, 2015; Kim, Lee, Kahng, & Kim, 2002).

2.2.1 Degree Centrality

Degree centrality is one of the basic indicators to study networks and is defined as, “the number of links connected to a node” (McCulloh, Armstrong, & Johnson, 2013). Degree centrality can be calculated as follows:

$$C_D(n_i) = \frac{\sum_{j=1}^n a(n_i, n_j)}{n-1}$$

where,

$C_D(n_i)$ is the degree centrality of a node i , $a(n_i, n_j)$ is the link between nodes i and j and n is the total number of nodes in the network (Kazemilari & Djauhari, 2015; McCulloh, Armstrong, & Johnson, 2013; Lee & Djauhari, 2012).

2.2.2 Closeness Centrality

According to McCulloh, Armstrong & Johnson (2013) closeness centrality can simply be stated as the inverse of the geodesic distances between a stock i and all the other stocks. It is an index of the time taken till the arrival of something flowing through the network. In terms of correlations, closeness centrality estimates how close a node is to all other nodes. It measures how long it takes information to spread from one node of a network to all the other nodes in the network. It can be estimated as:

$$C_C(n_i) = \frac{n-1}{\sum_{j=1}^n d(n_i, n_j)}$$

where,

$C_C(n_i)$ is the closeness centrality of a node i , $d(i, j)$ is the shortest path from node i to node j and n is the total number of nodes in the network (Kazemilari & Djauhari, 2015; Lee & Djauhari, 2012).

2.2.3 Geodesic Path and Geodesic Distance

A geodesic path is the shortest possible path between two nodes and geodesic distance is the length of the geodesic path.

2.2.4 Betweenness Centrality

Betweenness centrality is a measure of the extent to which a stock i lies on the geodesic paths between other stocks in the network (Badar, Hite, & Badir, 2013). Betweenness centrality is based on the notion that a node is central if it is needed to connect other pairs of nodes. This measure is calculated as follows:

$$C_B(n_i) = \frac{\sum_{j < k} g_{jk}(n_i) / g_{jk}}{(n-1)(n-2)/2}$$

where,

$C_B(n_i)$ is the betweenness centrality of a node i , g_{jk} is the number of geodesics linking the two nodes and $g_{jk}(n_i)$ is the number of geodesics linking the two nodes that contain node n_i (Kazemilari & Djauhari, 2015; McCulloh, Armstrong, & Johnson, 2013; Lee & Djauhari, 2012).

2.2.5 Node Strength

An important measure of the strength or weakness of the links between the nodes is node strength. It can be defined as, “the sum of the correlation coefficients of a node with all the other nodes” (Huang, Zhuang, Yao, & Ursayev, 2016; Wang & Xie, 2015; Kim, Lee, Kahng, & Kim, 2002). Node strength can be calculated as:

$$S_i^t = \sum_{j \in \Omega_i} \rho_{ij}^t$$

where,

Ω_i is the set of nodes connected to a node i .

3. Methodology

The below discussed methods were adopted to explore the stock network structures in KSE 100 Index of the PSX by visualizing the returns and volatility based networks and estimating

the measures of degree, closeness and betweenness centrality and node strength. The networks using stock returns and volatility of stock returns were developed from the cross-correlation matrices that were constructed using the methodology proposed by Soramaki & Cook (2016).

- (a) Calculated, for stationarity, the daily natural logarithmic return for every stock j , at time i , using the given equation;

$$r_{i,j} = \ln\left(\frac{p_{i,j}}{p_{i-1,j}}\right)$$

where, $r_{i,j}$ is the logarithmic stock return of asset j on day i and $p_{i,j}$ is the daily closing price of stock j at time i and $p_{i-1,j}$ is the last day closing price of stock j at time $i - 1$.

- (b) Estimated the volatility of a stock j at time i where the returns have zero mean;

$$V_{i,j} = \sqrt{\sum_{i=0}^{n-1} (1-\lambda)\lambda^i r_{n-i,j}^2}$$

where, $V_{i,j}$ is the volatility of a stock j at time i , λ is a constant having a value of 0.94 between 0 and 1, r^2 is the square of the returns of a stock j at a point in time $n - i$.

- (c) Constructed the returns based cross-correlation matrix $C_{j,k}$, of size $M \times M$, where the correlation coefficient between two stocks j and k is:

$$\text{Cor}_{j,k} = \frac{\sum_{i=1}^n (r_{i,j} - \bar{r}_j)(r_{i,k} - \bar{r}_k)}{V_j V_k}$$

where, \bar{r}_j is the sample mean of returns for stock j and \bar{r}_k is the sample mean of returns for stock k and V_j and V_k are the volatilities of stocks j and k .

- (d) Constructed the volatility based cross-correlation matrix $C_{j,k}$, of size $M \times M$, where the correlation coefficient between two stocks j and k is:

$$\text{Cor}_{j,k} = \frac{\sum_{i=0}^{n-1} (1-\lambda)\lambda^i r_{n-i,j} r_{n-i,k}}{V_j V_k}$$

- (e) The value of the correlation coefficient can vary from -1 to 1 for all stock correlations, where;

$$c_{xy} = \begin{cases} 1 \text{ means perfectly positively correlated} \\ 0 \text{ means no correlation} \\ -1 \text{ means perfectly negatively correlated (Mantegna, 1999).} \end{cases}$$

For developing the networks from the cross-correlation matrix, all stocks were set to be nodes of the network and correlations of returns were the links among the stocks. In order to convert the correlation matrix to a binary matrix for visualizing and calculating centralities, statistical significance testing was performed on the correlation matrices at the 5% level. Significance testing was conducted so that nodes and edges could be filtered based on statistical significance which, is required when the nodes or links are statistics calculated from data, for example, correlations.

Due to the large number of significance tests conducted, the Bonferroni Correction was applied for multiple testing. The application of Bonferroni Correction assigned a value of 0 to the correlations that were not statistically significant at the 5% level and assigned a value of 1 to the correlations that were statistically significant at the 5% level (Soramaki & Cook, 2016).

The centrality measures of degree, closeness and betweenness were calculated as mentioned by McCulloh, Armstrong & Johnson (2013):

(a) Degree centrality was calculated as follows:

$$C_D(n_i) = \frac{\sum_{j=1}^n a(n_i, n_j)}{n-1}$$

where,

$C_D(n_i)$ is the degree centrality of a node i , $a(n_i, n_j)$ is the link between nodes i and j and n is the total number of nodes in the network.

(b) Closeness centrality was calculated as follows:

$$C_C(n_i) = \frac{n-1}{\sum_{j=1}^n d(n_i, n_j)}$$

where,

$C_C(n_i)$ is the closeness centrality of a node i , $d(i, j)$ is the shortest path from node i to node j and n is the total number of nodes in the network.

(c) Betweenness centrality was calculated as follows:

$$C_B(n_i) = \frac{\sum_{j < k} g_{jk}(n_i) / g_{jk}}{(n-1)(n-2)/2}$$

where,

$C_B(n_i)$ is the betweenness centrality of a node i , g_{jk} is the number of geodesics linking the two nodes and $g_{jk}(n_i)$ is the number of geodesics linking the two nodes that contain node n_i .

Node strength was calculated by using the following method:

$$S_i^t = \sum_{j \in \Omega_i} \rho_{ij}^t$$

where,

Ω_i is the set of nodes connected to a node i (Huang, Zhuang, Yao, & Ursayev, 2016).

The stocks listed on the KSE 100 Index of the PSX were the sample for this study from the year 2000 to year 2018. The selected sample comprises of the 100 most sensitive stock prices that develop the most important spot price index, that is, the KSE 100 Index, of the PSX. Secondary data for this study was gathered. The source was the website of PSX (www.psx.com.pk). The returns of the daily closing prices of the stocks listed on the PSX index of KSE 100 were taken for constructing the yearly networks from 2000 to 2018. This time-period was selected because data of the individual hundred stocks for the said tenure was available on the PSX website. The data for the individual stocks for the give time-period listed on the KSE 100 index was not available on any other free of cost online source. A total of 240 working days was used per year (Chen, Luo, Sun, & Wang, 2015). The data was entered and stored in a spreadsheet program for developing the cross-correlation matrices. UCINET (VI) (Borgatti, Everett, & Freeman, 2002) software was used to develop, visualize and analyze the networks.

4. Results

The networks were constructed for every year, from 2000 to 2018, which make a total of 19 networks. In the networks developed, the nodes were the stocks listed on the KSE 100 Index of the PSX and the edges (links) among the stocks were the correlations that were estimated using the stock returns and stock returns volatility. The number of stocks and links were calculated for every network each year whereas, the average degree, closeness and betweenness centrality and average node strength were estimated for the entire time-period for every stock. In the networks constructed, the highest value of degree centrality shows that a stock has the maximum number of links with all the other stocks and holds a central position in the network. The lowest value of degree centrality shows that a stock has the minimum number of links with all the other stocks and has a weak position in the network. The highest value of closeness centrality describes that a stock is the closest to all the other stocks in the network thus, making it an important stock in the network for quickly transferring the changes occurring in the network. A low value of closeness centrality means that a stock is far away from all the other stocks in the network making it a less important stock for transferring the changes occurring in the network. A high value of betweenness centrality shows that a stock lies on the maximum number of shortest paths that connect two stocks in the network thereby, making this stock an important bridge that links two stocks. A low betweenness centrality means that the stock does not lie on the maximum number of shortest paths in the network and does not hold an important position in the network. A high value of node strength means that a stock is strongly correlated with all the other stocks in the networks whereas, a low value of node strength shows that a stock is weakly correlated with all the other stocks in the network.

4.1 Comparing Returns based Networks and Volatility based Networks

The comparison of returns based networks and volatility based networks helped to better understand the structure of the networks. Comparing the two types of networks helped to decide which measure, that is stock returns or volatility of stock returns, is a better measure and must be used to construct the networks. By comparing the returns and volatility networks, inferences can be made as to which type of networks provides more and useful information regarding the stock market.

Years	Stocks	Links (Returns Networks)	Links (Volatility Networks)
2000	62	3044	1698
2001	65	3342	2604
2002	69	4318	2682
2003	72	4986	5088
2004	77	5688	5210
2005	82	6336	5380
2006	82	3608	868
2007	84	5960	3084
2008	85	5176	6006
2009	86	6690	7040
2010	86	4720	362

2011	89	7130	6360
2012	90	7920	6810
2013	91	8188	8184
2014	94	8726	8734
2015	97	9268	9298
2016	98	7646	446
2017	100	5358	2448
2018	100	5340	598

Table 4.1 Comparison of Returns based and Volatility based Networks

The comparison of returns based and volatility based networks is shown in Table 4.1. First column of the table shows the years for each network, second column shows the number of stocks for each year's network, the third column shows the number of links in each year's returns network and the fourth column shows the number of links in each year's volatility network.

For the same number of stocks, the number of links present a clear difference between the two types of networks. In the years when the PSX was performing well, such as 2013, 2014 and 2015 there is not much difference between the number of links among the stocks of the two types of networks.

But for the years when the market was not performing well and there was a slowdown in the trading activities was due to the assassination of the Baloch leader Nawab Akbar Khan Bugti in an army operation on August 26, 2006 (Nazir, Younus, Kaleem, & Anwar, 2014; Gul, Khan, Saif, Rehman, & Roohullah, 2013). the assassination of the Ex-Prime Minister, Benazir Bhutto on December 27, 2007 and the US sub-prime crisis (Hira, 2017; Najaf, 2017; Nazir, Younus, Kaleem, & Anwar, 2014; Ali & Afzal, 2012; Draz, 2011), a series of terrorist activities across the country during the entire year of 2010 (Bilal, Abu Talib, & Haq, 2012), the leak of Panama Papers in 2016 that restarted the political unrest in the country (Rehman, Burhan, & Khan, 2018) and the disqualification of Prime Minister Nawaz Sharif on July 28, 2017. The difference between the number of links among the stocks of the returns and volatility networks is very significant in the years. Although, the number of links in the returns networks had decreased during these years but the intensity of decline in the number of links of volatility networks is greater. The difference can be observed from Table 4.1 for the years 2006, 2007, 2010, 2016 and 2018. The links among the stocks in the volatility networks are fewer than the links among the stocks in returns networks. This shows that volatility networks only show the most significant links among the stocks whereas the returns networks fail to do the same for the stock network structures. Volatility networks provide more useful information regarding the relations among the stocks as compared to the returns networks.

For the rest of the years, the differences between the number of links among the stocks in the two types of networks show that if the stock market is performing well the links among the stocks in volatility networks are greater than the links among stocks in returns networks and if the stock market is not doing well the links among the stocks in volatility networks are lower than the links among stocks in returns networks. Therefore, it can be inferred that a

slowdown in the trading activities at the stock market affects the volatility networks more than the returns networks because the volatility based correlations among stocks are more sensitive to shocks than the returns based correlations (Kenett & Havlin, 2015; Lyocsa, Vyrost, & Baumohl, 2012).

4.2 Comparing the Centrality Metrics and Node Strength

The comparison between the returns based and volatility based networks for the different centrality metrics and node strength can be observed from Figure 4.1 to Figure 4.4.

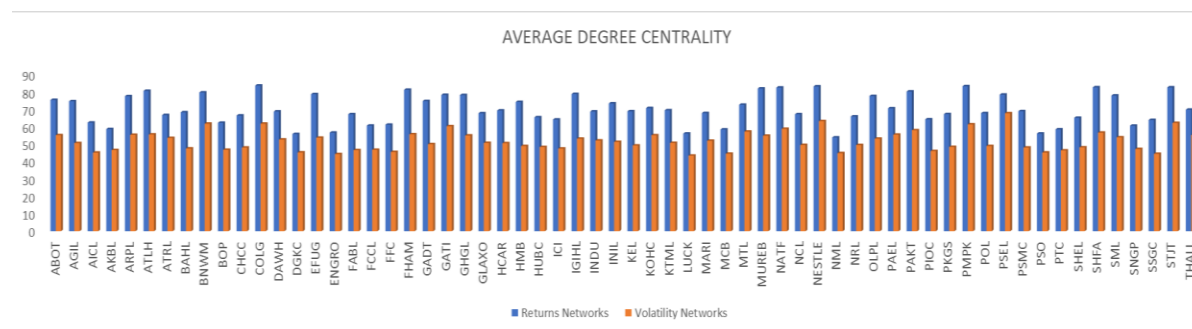


Figure 4.1 Average Degree Centrality

Figure 4.1 shows the average degree centrality of the stocks in both returns and volatility based networks. The blue bars represent the returns based networks and the orange bars represent the volatility based networks. It can be observed that in the returns based networks the stock Colgate-Palmolive (COLG) has the highest average degree centrality and the stock Nishat Mills Limited (NML) has the lowest average degree centrality whereas, in the volatility based networks the stock Pakistan Services Limited (PSEL) has the highest average degree centrality and Lucky Cement Limited (LUCK) has the lowest average degree centrality.

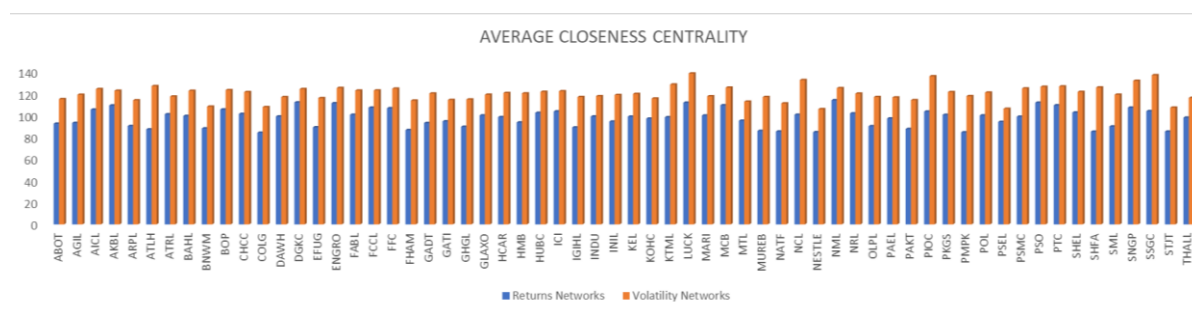
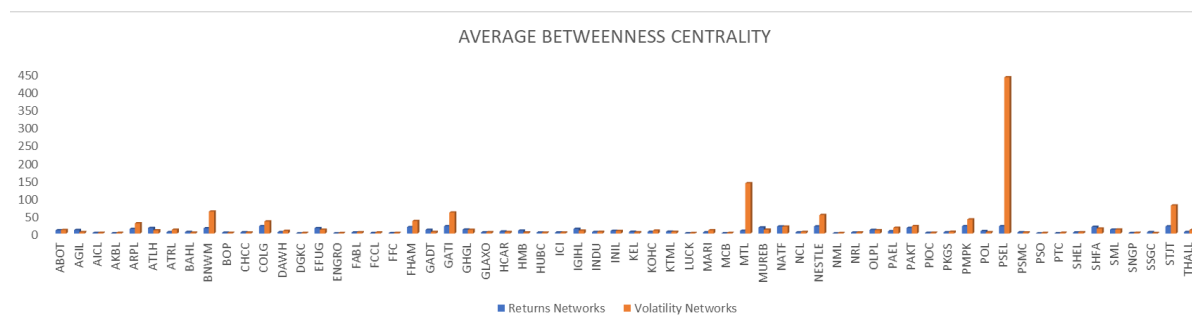


Figure 4.2 Average Closeness Centrality

Figure 4.2 shows the average closeness centrality of the stocks in both returns and volatility based networks. The blue bars represent the returns based networks and the orange bars represent the volatility based networks. It can be observed that in the returns based networks the stock Nishat Mills Limited (NML) has the highest average closeness centrality and the stock Colgate-Palmolive (COLG) has the lowest average closeness centrality whereas, in the volatility based networks the stock Lucky Cement Limited (LUCK) has the highest



average closeness centrality and Nestle (NESTLE) has the lowest average closeness centrality.

Figure 4.3 Average Betweenness Centrality

Figure 4.3 shows the average betweenness centrality of the stocks in both returns and volatility based networks. The blue bars represent the returns based networks and the orange bars represent the volatility based networks. It can be observed that in the returns based networks the stock Colgate-Palmolive (COLG) has the highest average betweenness centrality and the stock Nishat Mills Limited (NML) has the lowest average betweenness centrality whereas, in the volatility based networks the stock Pakistan Services Limited (PSEL) has the highest average betweenness centrality and Engro Corporation (ENGRO) has the lowest average betweenness centrality.

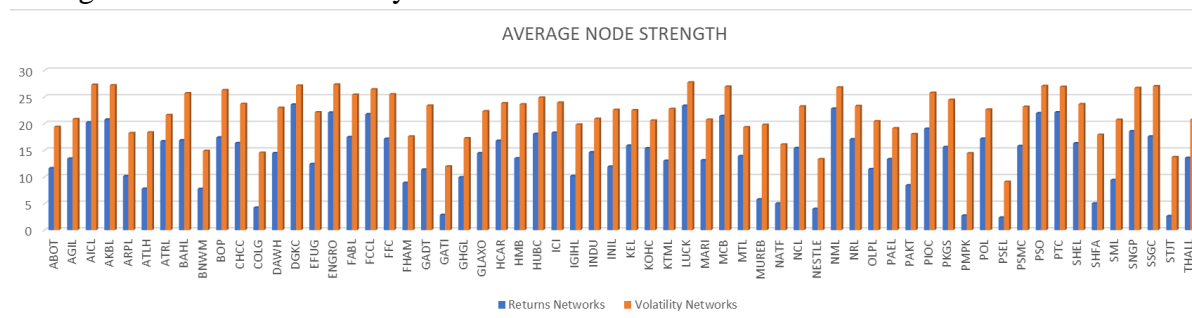


Figure 4.4 Average Node Strength

Figure 4.4 shows the average node strength of the stocks in both returns and volatility based networks. The blue bars represent the returns based networks and the orange bars represent the volatility based networks. It can be observed that in the returns based networks the stock D.G. Khan Cement Company Limited (DGKC) has the highest average node strength and the stock Pakistan Services Limited (PSEL) has the lowest average node strength whereas, in the volatility based networks the stock Lucky Cement Limited (LUCK) has the highest average node strength and Pakistan Services Limited (PSEL) has the lowest average node strength.

5. Conclusion

The motivation for this research was to explore the stock network structures in the PSX using two measures, stock returns and stock returns volatility, and apply the centrality metrics and node strength from network theory on the explored networks. The data for 100 stocks with the highest market capitalization listed on the KSE 100 index in the PSX was obtained from the years 2000 to 2018.

It was inferred from the comparison of the stock networks formed using stock returns and stock returns volatility that the later networks provide more useful information by only identifying the strongest and important links in a network. The networks constructed using stock returns neither included the strong links in times when the stock market was bullish nor removed the weak links in times when the stock market was bearish after applying the network filtration whereas, only strongest links were left in the volatility based networks whether the stock market was bullish or bearish after network filtration.

The centrality metrics of degree, closeness and betweenness along with node strength were applied on the explored networks of the PSX. It is concluded from the results that on average only a few stocks, that are, Colgate-Palmolive (COLG), Nishat Mills Limited (NML) and D.G. Khan Cement Company Limited (DGKC) hold the important structural positions in the returns based stock networks, whereas, Pakistan Services Limited (PSEL) and Lucky Cement Limited (LUCK) hold the important structural positions in the volatility based networks. The volatility based networks provide more useful and specific information as PSEL has the highest average degree and betweenness centrality implying that it has the maximum links with other stocks and mostly lies on the geodesic path linking two stocks. LUCK has the highest average closeness centrality making it the stock most close to all the other stocks in the network and the highest average node strength stating that LUCK has the strongest links with all the other stocks in the network. The same inferences cannot be made about the returns based networks as various stocks hold the important structural positions in the returns based networks.

It is concluded that the Pakistan Stock Exchange (PSX), a stock market of an emerging economy, is dominated by only a few stocks that can manipulate the entire stock market, thus making it a shallow market. The results of this study are in line with the previous studies (Dimitrios & Vasileios, 2015; Namaki, Shirazi, Raei & Jafari, 2011; Tse, Liu & Lau, 2010; Huang, Zhuang & Yao, 2009; Tabak, Takami, Cajueiro & Petitinga, 2009).

The practical implications of this study are important for the investors and portfolio managers as it provides specific and imperative information about the most important stocks. Also, the whole stock market directed by some stocks decreases the price efficiency, providing opportunities to the stakeholders to take advantage of such mispricing and achieve abnormal returns. The theoretical implications include the introduction of stock networks constructed using stock returns volatility, exploration of the stock network structures of the PSX and application of the centrality metrics and node strength on the stock networks of the PSX. Further research can be carried out by applying other tools and techniques from network theory and by considering all the stocks listed on the PSX.

References

- Ali, R., & Afzal, M. (2012). Impact of Global Financial Crisis on Stock Markets: Evidence from Pakistan and India. *E3 Journal of Business Management and Economics*, **3**(7), 275-282. Retrieved from http://www.e3journals.org/cms/articles/1342846725_Afzal.pdf
- Badar, K., Hite, J. M., & Badir, Y. F. (2013). Examining the Relationship of Co-Authorship Network Centrality and Gender on Academic Research Performance: The Case of Chemistry Researchers in Pakistan. *Scientometrics*, **94**(2), 755-775. doi:<https://doi.org/10.1007/s11192-012-0764-z>
- Bilal, A. R., Abu Talib, N. B., & Haq, I. U. (2012). How Terrorism and Macroeconomic Factors Impact on Returns: A Case Study of Karachi Stock Exchange. *World Applied Sciences Journal*, **19**(11), 1575-1584. doi:10.5829/idosi.wasj.2012.19.11.2611
- Borgatti, S. P., Everett, M. G., & Freeman, L. C. (2002). *UCINET for Windows: Software for Social Network Analysis*. Harvard, MA: Analytic Technologies, 6.
- Cayley, A. (1889). *The Collected Mathematical Papers of Arthur Cayley*. London: Cambridge University Press.
- Chen, K., Luo, P., Sun, B., & Wang, H. (2015). Which Stocks are Profitable? A Network Method to Investigate the Effects of Network Structure on Stock Returns. *Physica A: Statistical Mechanics and its Applications*, **436**, 224-235. doi:<https://doi.org/10.1016/j.physa.2015.05.047>
- Derrible, S., & Kennedy, C. (2011). Applications of Graph Theory and Network Science to Transit Network Design. *Transport Reviews*, **31**(4), 495-519. doi:<https://doi.org/10.1080/01441647.2010.543709>
- Dimitrios, K., & Vasileios, O. (2015). A Network Analysis of the Greek Stock Market. *Procedia Economics and Finance*, **33**, 340-349. doi:[https://doi.org/10.1016/S2212-5671\(15\)01718-9](https://doi.org/10.1016/S2212-5671(15)01718-9)
- Draz, M. U. (2011). Impact of Financial Crises on Pakistan and China: A Comparative Study of Six Decades. *Journal of Global Business and Economics*, **3**(1), 174-186. Retrieved from <https://ssrn.com/abstract=1804410>
- Estrada, E. (2014). Graph and Network Theory. In M. Grinfeld, *Mathematical Tools for Physicists* (pp. 111-157). Glasgow: Wiley-VCH Verlag GmbH & Co. KGaA. doi:<https://doi.org/10.1002/3527600434.eap726>
- Euler, L. (1741). *Solutio Problematis ad Geometriam Situs Pertinentis* [The Solution to a Problem Relating to the Geometry of Position]. *Commentarii Academiae Scientiarum Petropolitanae*, **8**, 128-140. Retrieved from <https://scholarlycommons.pacific.edu/cgi/viewcontent.cgi?article=1052&context=euler-works>
- Freeman, L. C. (1977). A Set of Measures of Centrality Based on Betweenness. *Sociometry*, **40**(1), 35-41.
- Gul, S., Khan, M. T., Saif, N., Rehman, S. U., & Roohullah. (2013). Stock Market Reaction to Political Events (Evidence from Pakistan). *Journal of Economics and Sustainable Development*, **4**(1), 165-174.
- Hira, I. (2017). Relationship among Political Instability, Stock Market Returns and Stock Market Volatility. *Studies in Business and Economics*, **12**(2), 70-99.

- Hu, D., Schwabe, G., & Li, X. (2015). Systemic Risk Management and Investment Analysis with Financial Network Analytics: Research Opportunities and Challenges. *Financial Innovation*, **1**(2), 1-9. doi:<https://doi.org/10.1186/s40854-015-0001-x>
- Huang, W. Q., Zhuang, X. T., & Yao, S. (2009). A Network Analysis of the Chinese Stock Market. *Physica A: Statistical Mechanics and its Applications*, **388**(14), 2956-2964. doi:<https://doi.org/10.1016/j.physa.2009.03.028>
- Huang, W. Q., Zhuang, X. T., Yao, S., & Ursayev, S. (2016). A financial network perspective of financial institutions' systemic risk contributions. *Physica A*, **456**, 183-196.
- Jung, W.-S., Chae, S., Yang, J.-S., & Moon, H.-T. (2006). Characteristics of the Korean Stock Market Correlations. *Physica A: Statistical Mechanics and its Applications*, **361**(1), 263-271.
- Kazemilari, M., & Djauhari, M. A. (2015). Correlation Network Analysis for Multi-Dimensional Data in Stocks Market. *Physica A: Statistical Mechanics and its Applications*, **429**, 62-75.
- Kenett, D. Y., & Havlin, S. (2015). Network Science: A Useful Tool in Economics and Finance. *Mind & Society*, **14**(2), 155-167.
- Kim, H. J., Lee, Y., Kahng, B., & Kim, I. M. (2002). Weighted scale-free network in financial correlations. *Journal of the Physical Society of Japan*, **71**(9), 2133-2136.
- Lee, G. S., & Djauhari, M. A. (2012). An Overall Centrality Measure: The Case of U.S Stock Market. *International Journal of Basic & Applied Sciences*, **12**(6), 99-103.
- Lyocsa, S., Vyrost, T., & Baumohl, E. (2012). Stock Market Networks: The Dynamic Conditional Correlation Approach. *Physica A: Statistical Mechanics and its Applications*, **391**(16), 4147-4158.
- Mantegna, R. N. (1999). Information and Hierarchical Structure in Financial Markets. *Computer Physics Communications*, **121-122**, 153-156.
- McCulloh, I., Armstrong, H., & Johnson, A. (2013). *Social Network Analysis with Applications*. New Jersey: John Wiley & Sons, Inc.
- Moghadam, H. E., Mohammadi, T., Kashani, M. F., & Shakeri, A. (2019). Complex Networks Analysis in Iran Stock Market: The Application of Centrality. *Physica A: Statistical Mechanics and its Applications*, **531**, 121800.
- Najaf, R. (2017). Asymmetric Impact of Financial Crisis on Stock Exchange of Malaysia and Pakistan. *Case Studies Journal*, **6**(3), 5-10.
- Namaki, A., Shirazi, A. H., Raei, R., & Jafari, G. R. (2011). Network analysis of a financial market based on genuine correlation and threshold method. *Physica A*, **390**(21-22), 3835-3841.
- Nazir, M. S., Younus, H., Kaleem, A., & Anwar, Z. (2014). Impact of Political Events on Stock Market Returns: Empirical Evidence from Pakistan. *Journal of Economic and Administrative Sciences*, **30**(1), 60-78.
- Nie, H., Zhang, Y. B., Chen, J. R., & Lv, X. G. (2015). Research of Chinese Stock Market' Complex Network Structure. **7**(5), 116-124.
- Rehman, S. u., Burhan, M., & Khan, S. A. (2018). Impact of CPEC, Panama Leak and Surgical Strike on Stock Market. *Bahria University Journal of Management & Technology*, **2**(1), 6-26.

- Rodrigue, J. P., & Ducruet, C. (2017). Graph Theory: Definition and Properties. In J. P. Rodrigue, C. Comtois, & B. Black, *The Geography of Transport Systems* (pp. 304-306). New York: Routledge.
- Sharif, S., & Djauhari, M. A. (2012). A Proposed Centrality Measure: The Case of Stocks Traded at Bursa Malaysia. *Modern Applied Science*, **6**(10), 62-69.
- Soramaki, K., & Cook, S. (2016). *Network Theory and Financial Risk*. London: Risk Books, Incisive Media Investments Ltd.
- Tabak, B. M., Serra, T. R., & Cajueiro, D. O. (2010). Topological Properties of Stock Market Networks: The Case of Brazil. *Physica A: Statistical Mechanics and its Applications*, **389**(16), 3240-3249.
- Tabak, B. M., Takami, M. Y., Cajueiro, D. O., & Petitinga, A. (2009). Quantifying Price Fluctuations in the Brazilian Stock Market. *Physica A: Statistical Mechanics and its Applications*, **388**(1), 59-62. doi:https://doi.org/10.1016/j.physa.2008.09.028
- Tse, C. K., Liu, J., & Lau, F. C. (2010). A Network Perspective of the Stock Market. **17**(4), 659-667.
- Vizgunov, A., Goldengorin, B., Kalyagin, V., Koldanov, A., Koldanov, P., & Pardalos, P. M. (2014). Network Approach for the Russian Stock Market. *Computational Management Science*, **11**(1-2), 45-55.
- Wang, G. J., & Xie, C. (2015). Correlation structure and dynamics of international real estate securities markets: A network perspective. *Physica A*, **424**, 176-193.
- Zhang, W., & Zhuang, X. (2019). The Stability of Chinese Stock Network and its Mechanism. *Physica A: Statistical Mechanics and its Applications*, **515**, 748-761.

Appendix A: Stock networks developed using stock returns

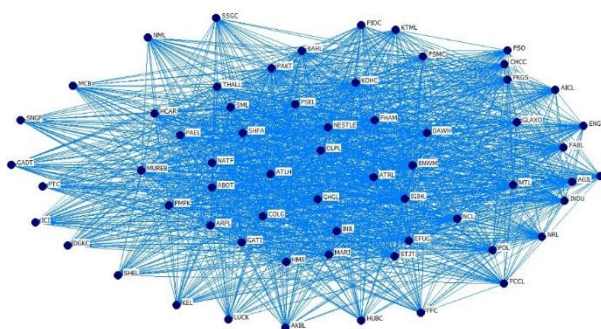


Figure 1 Year 2000 (Stocks = 62; Links = 3044)

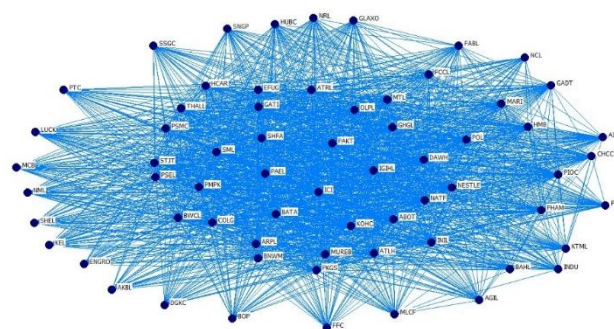


Figure 2 Year 2001 (Stocks = 65; Links = 3342)

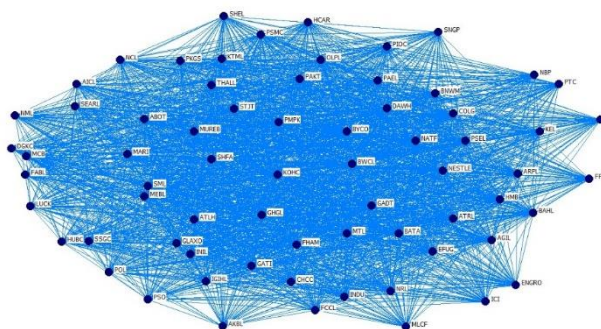


Figure 3 Year 2002 (Stocks = 69; Links = 4318)

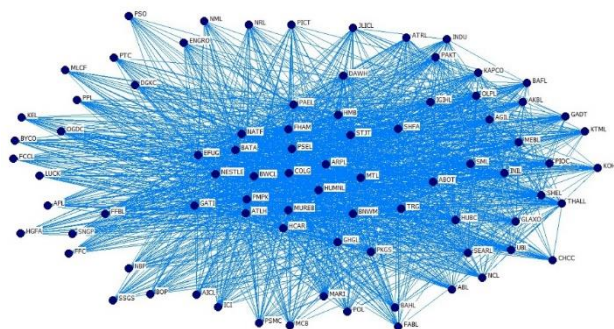


Figure 7 Year 2006 (Stocks = 82; Links = 3608)

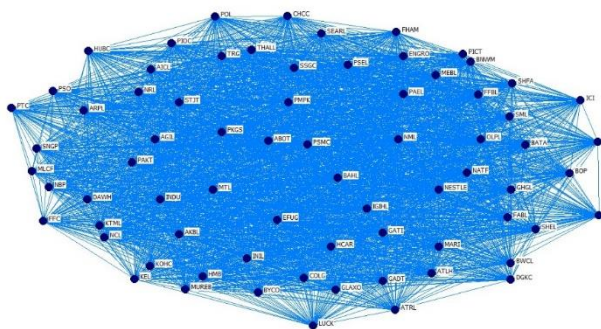


Figure 4 Year 2003 (Stocks = 72; Links = 4986)

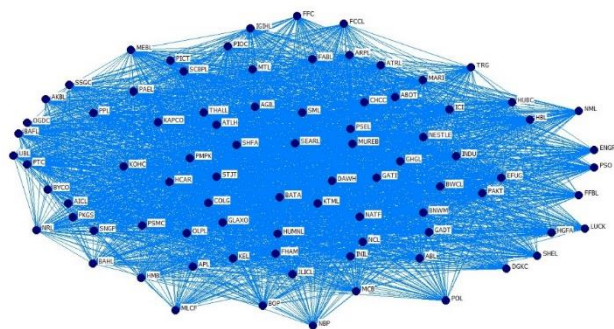


Figure 8 Year 2007 (Stocks = 84; Links = 5960)

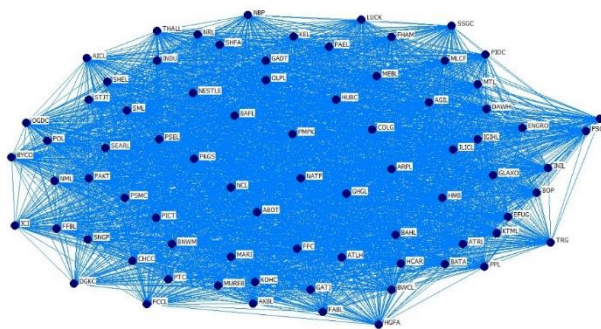


Figure 5 Year 2004 (Stocks = 77; Links = 5688)

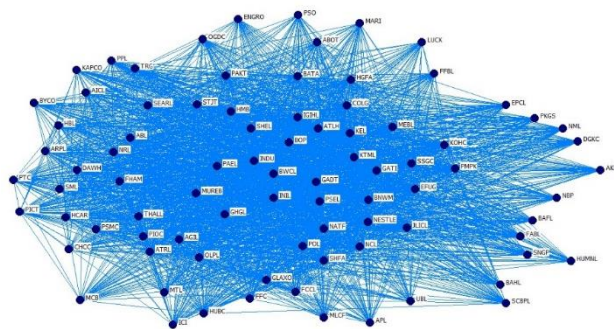


Figure 9 Year 2008 (Stocks = 85; Links = 5176)

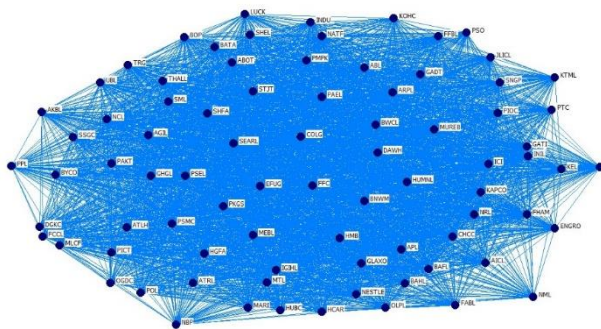


Figure 6 Year 2005 (Stocks = 82; Links = 6336)

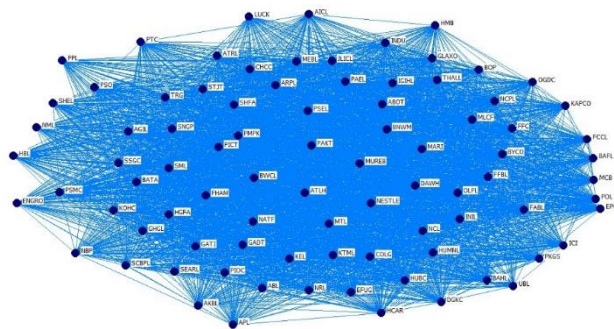


Figure 10 Year 2009 (Stocks = 86; Links = 6690)

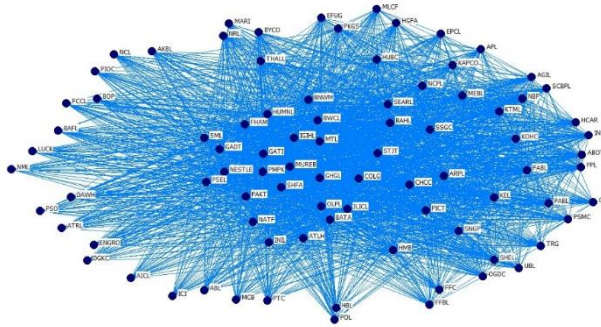


Figure 11 Year 2010 (Year 2010; Stocks = 86; Links = 4720)

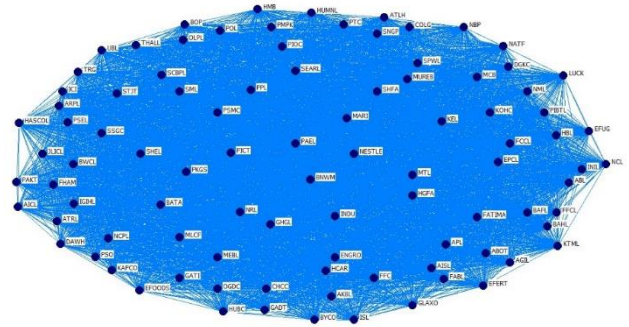


Figure 15 Year 2014 (Stocks = 94; Links = 8726)

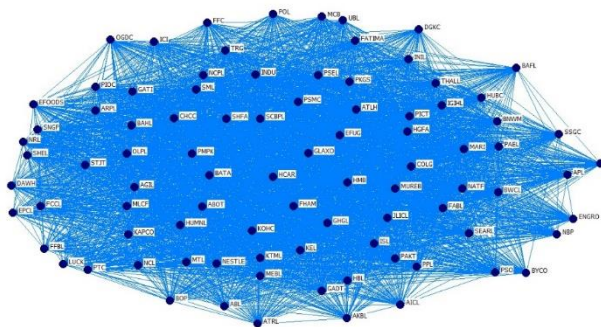


Figure 12 Year 2011 (Stocks = 89; Links = 7130)

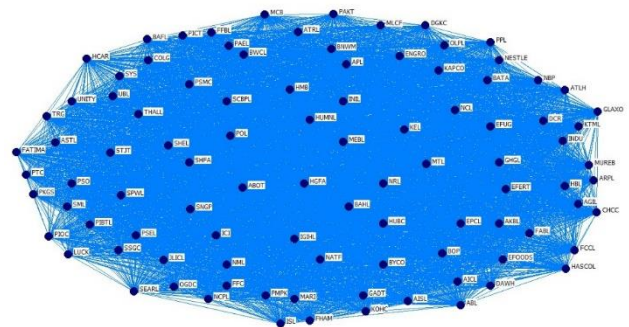


Figure 16 Year 2015 (Stocks = 97; Links = 9268)

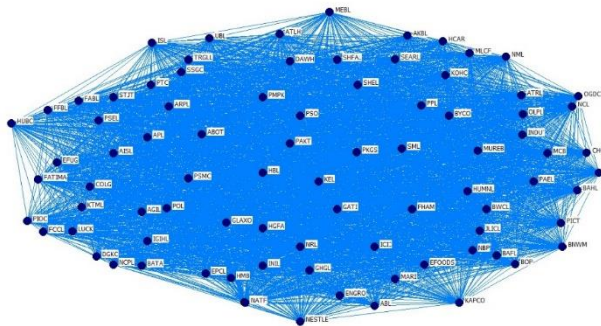


Figure 13 Year 2012 (Stocks = 90; Links = 7920)

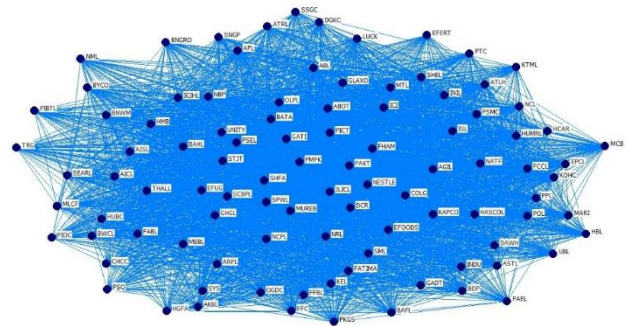


Figure 17 Year 2016 (Stocks = 98; Links = 7646)

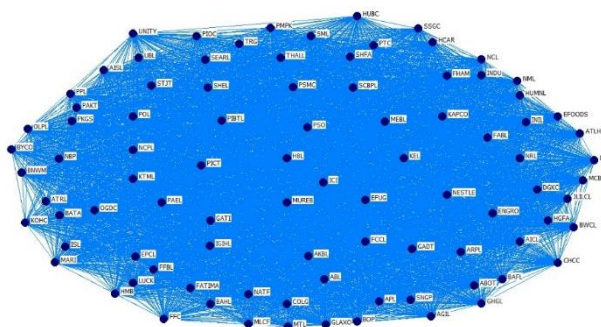


Figure 14 Year 2013 (Stocks = 91; Links = 8188)

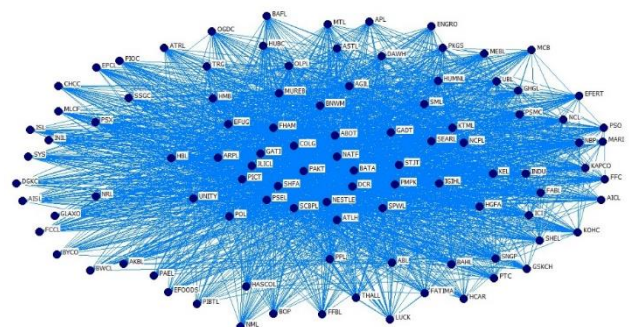


Figure 18 Year 2017 (Stocks = 100; Links = 5358)

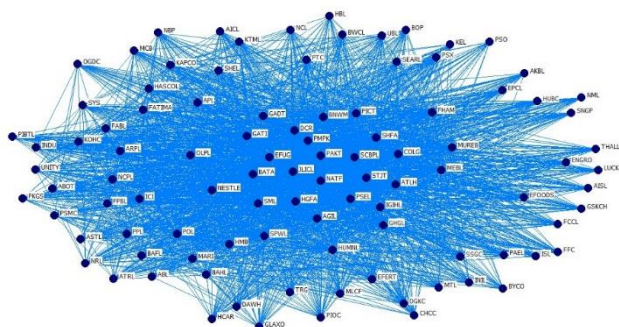


Figure 19 Year 2018 (Stocks = 100; Links = 5340)

Appendix B Stock networks developed using stock return volatilities

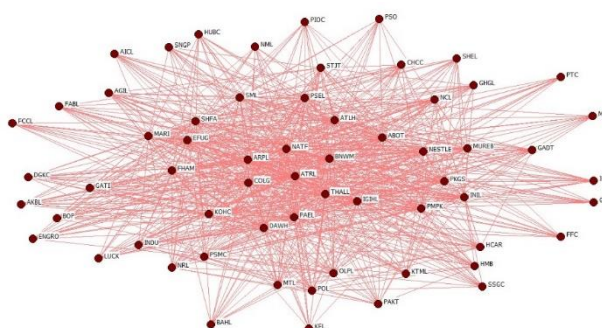


Figure 1 Year 2000 (Stocks = 62; Links = 1698)

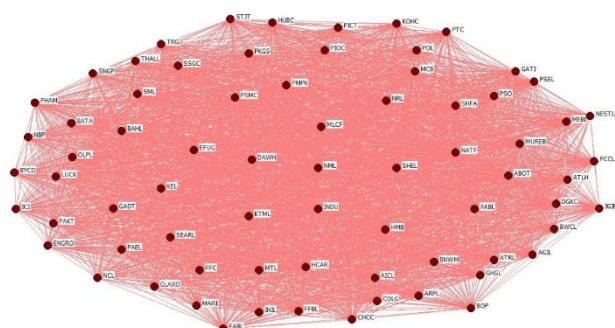


Figure 4 Year 2003 (Stocks = 72; Links = 5088)

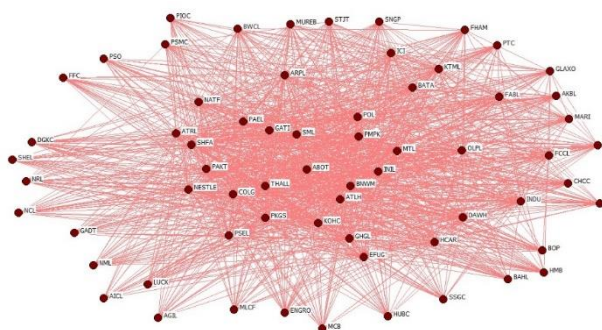


Figure 2 Year 2001 (Stocks = 65; Links = 2604)

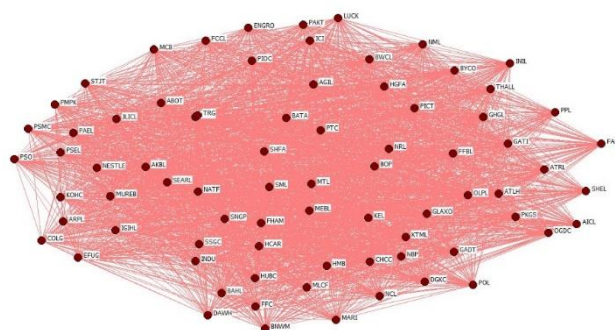


Figure 5 Year 2004 (Stocks = 77; Links = 5210)

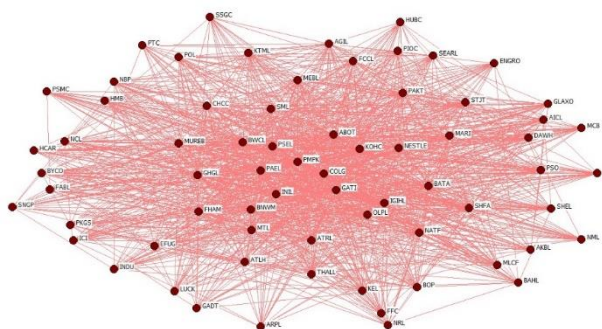


Figure 3 Year 2002 (Stocks = 69; Links = 2682)

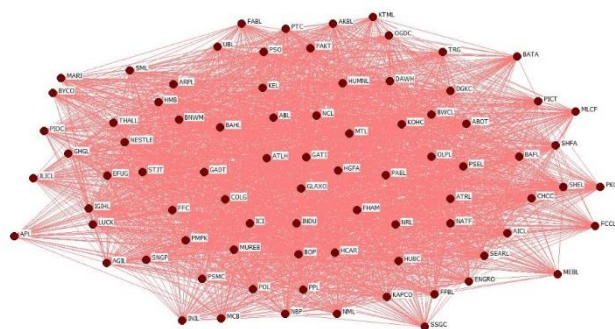


Figure 6 Year 2005 (Stocks = 82; Links = 5380)

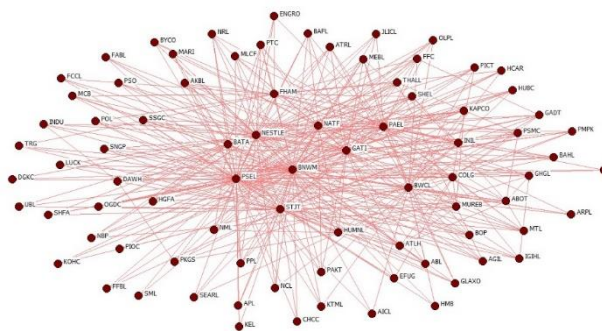


Figure 7 Year 2006 (Stocks = 82; Links = 868)

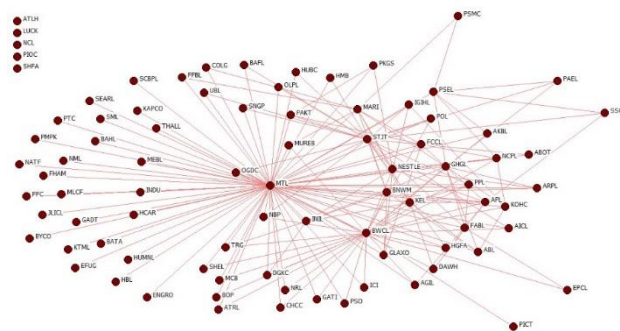


Figure 11 Year 2010 (Stocks = 86; Links = 362)

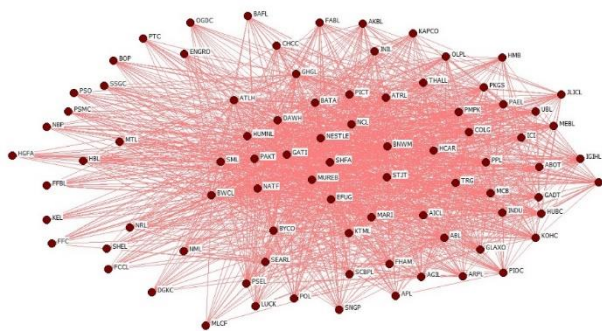


Figure 8 Year 2007 (Stocks = 84; Links = 3084)

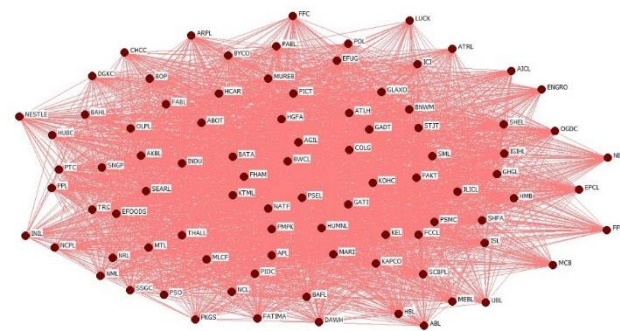


Figure 12 Year 2011 (Stocks = 89; Links = 6360)

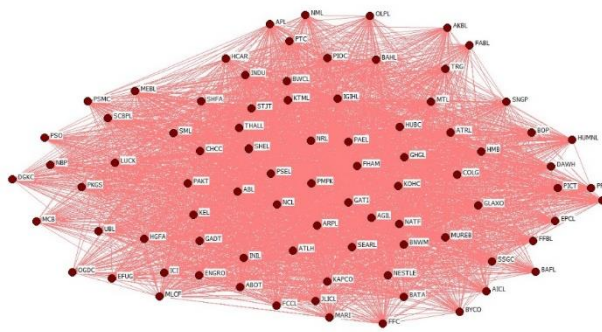


Figure 9 Year 2008 (Stocks = 85; Links = 6006)

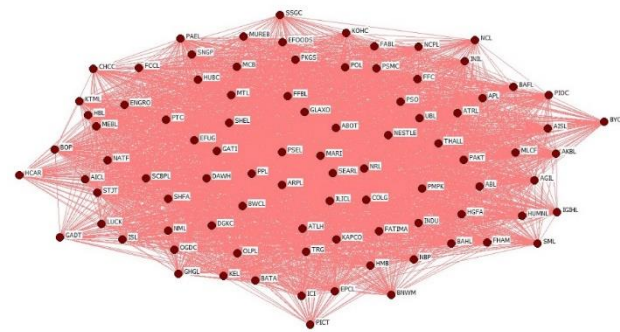


Figure 13 Year 2012 (Stocks = 90; Links = 6810)

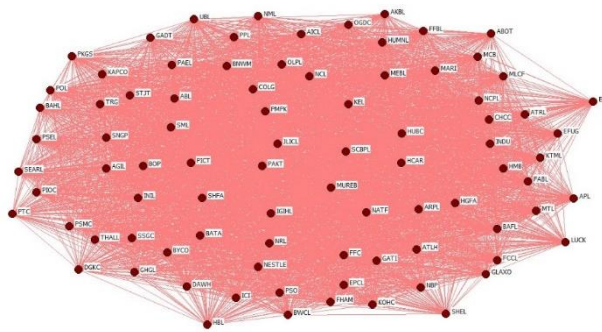


Figure 10 Year 2009 (Stocks = 86; Links = 7040)

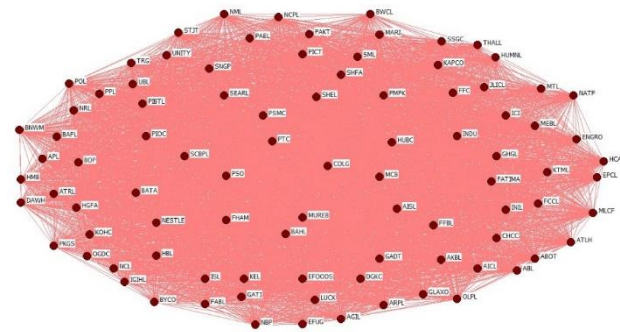


Figure 14 Year 2013 (Stocks = 91; Links = 8184)

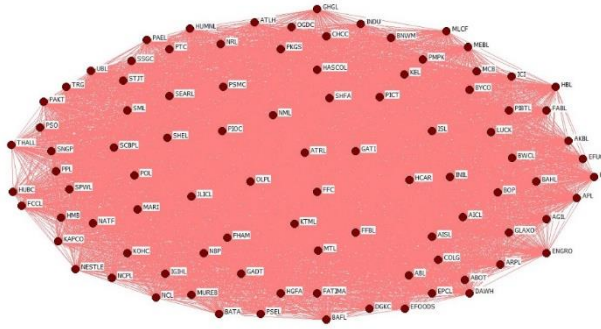


Figure 15 Year 2014 (Stocks = 94; Links = 8734)

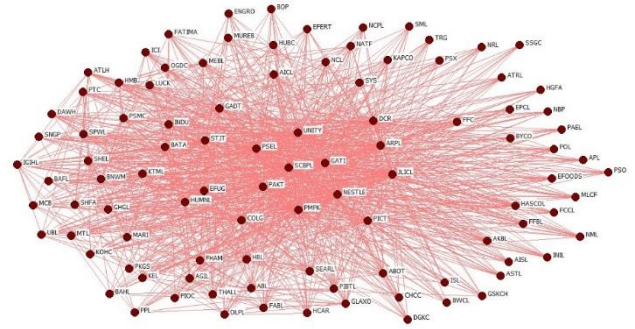


Figure 18 Year 2017 (Stocks = 100; Links = 2448)

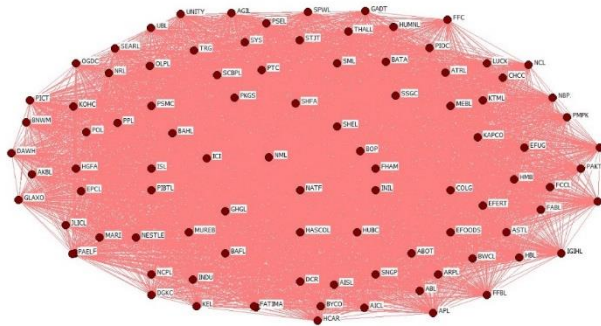


Figure 16 Year 2015 (Stocks = 97; Links = 9298)

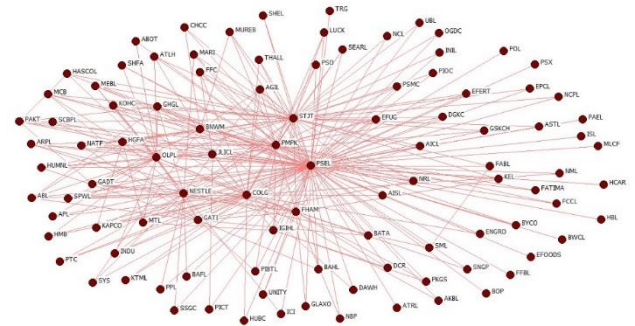


Figure 19 Year 2018 (Stocks = 100; Links = 598)

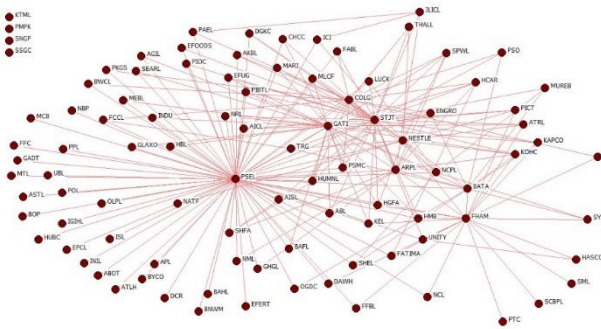


Figure 17 Year 2016 (Stocks = 98; Links = 446)