Stock Network Structures In The Pakistan Stock Exchange

Nadir Khan[*], Jameel Ahmed[†] and Saubia Ramzan[‡]

Abstract

This study adopts a new technique from the area of Network Theory to analyze and understand the relationships among the stocks of KSE 100 Index in the Pakistan Stock Exchange (PSX). The stock networks were developed using the stock returns and stock returns volatility and the dynamic threshold method was used to extract the important relationships in the networks.Supported by literature, the findings of this study show that as the threshold limit was increased the relationships among stocks started to disappear andit is concluded that volatility networks provide more useful information about the stock network structures as compared to the returns networks.The implications of the study are that the PSX is a scale-free network where the entire stock market is influenced by only a few strong stocks in the market.

Keywords: Network Theory, Stock Network Structures, KSE 100 Index, Capital Markets, Pakistan Stock Exchange (PSX).

Introduction

Stock market is one of the most complex financial networks being studied in the theory of finance due to the large amount of availabledata. A financial network is agraph, 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 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 conclude that the stock markets 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).

This study analyzed the stock network structures in the Pakistan Stock Exchange (PSX) and is distinctas it adopts returns as well as volatility as a measure to generate the cross-correlation matrices and develop the networks. The PSX being the emerging and only stock market of an Asian country is important to study because more research is needed to gain a better understanding of the definite

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behavior of Asian stock markets (Ahmed, Ahmed, Vveinhardt & Streimikiene, 2016).

Literature Review

An area of study that has received much attention now-a-days is the subject of Network Theory (Streib, et al., 2018). A comparative analysis of the Dow Jones Industrial Average (DJIA) and the Tehran Stock Exchange (TSE) showed that the stock networks in the TSE are scale-free networks and follow a power-law model (Namaki, et al., 2011). The network analysis of the US stockmarket concluded that the market was dominated heavily by a small number of stocks (Tse, et al., 2010).

Analysis of the stock networks in the Greek Stock Market one year before and during the financial crisis for years 2007 and 2012 showed that the Greek Stock Market is easily influenced by a few strong investors (Dimitrios & Vasileios, 2015).Study of the Chinese Stock Market found that stocks that have a higher status in the network have a higher profit value and the small-world characteristics of stock network is obvious (Nie, Zhang, Chen & Lv, 2015). A market graph model was used for the Russian Stock Market. The most important finding of the study was that the most attractive Russian stocks had the strongest correlations between their returns (Khan et al., 2013; Vizgunov, Goldengorin, Kalyagin, Koldanov, Koldanov, Pardalos, 2014).A study on the stock network structure of the Korean Stock Market showed that the Korean Stock Market is characteristically different from the mature stock markets of the world, such as the American stock markets (Jung, Chae, Yang & Moon, 2006).

Methodology

The population of the study were all the stocks listed on the KSE 100 Index of the PSX. The sampling technique used for obtaining secondary data was the online source, that is, the Data Portal of the PSX (https://dps.psx.com.pk/) for the listed companies on the KSE 100 Index for the time span 2000-2018. The data of 100 stocks was downloaded but the complete data of only 65 stocks was available. 25 stocks were discarded due to the unavailability of the data.

The closing prices of the stocks were used to calculate the logarithmic returns using the following formula:

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

where, $r_{i,j}$ is the natural log stock return of stock $_j$ 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 $i - 1$.

Correlation between two stocks was estimated with the following formula:

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

where, $\overline{r_j}$ is the sample mean of returns for stock *j* and $\overline{r_k}$ is the sample mean of returns for stock *k* and $V_j$and V_k are the volatilities of stocks *j* and *k*.

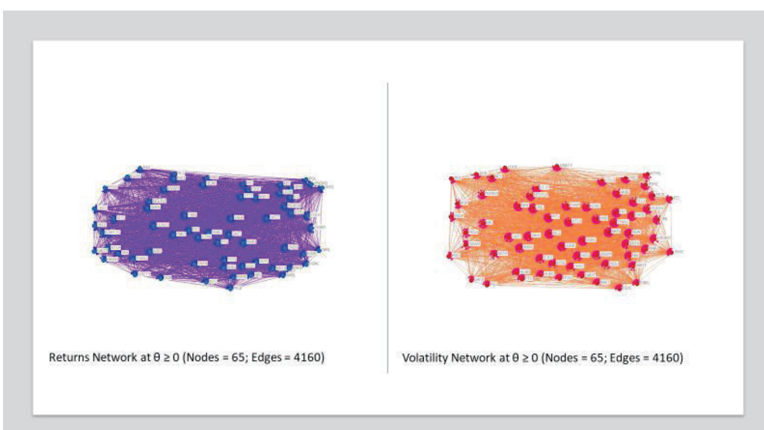
Volatility and volatility based cross-correlation matrices were developed using the Risk Metrics Methodology as proposed by J.P. Morgan and Reuters in the year 1996.

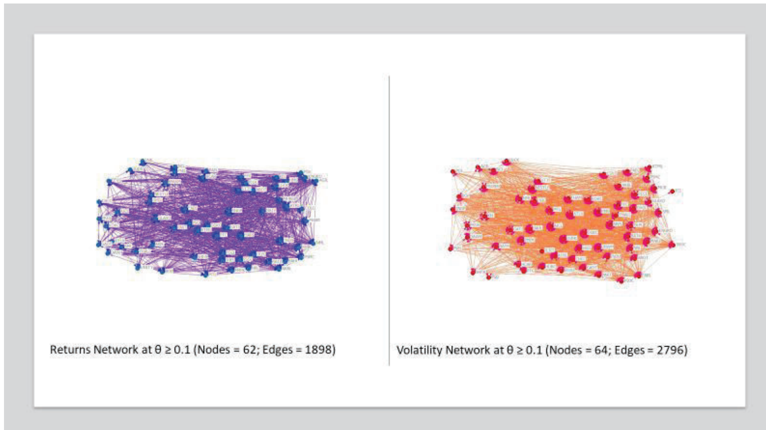
The stock networks were constructed from the cross-correlation matriceswhich were formulated using stock returns and stock returns volatility. As correlation has a value between -1 and +1, therefore, to convert the correlation matrix to a binary matrix, the absolute value of the correlations above the threshold θwere assigned the value of 1 whereas, the correlations below the threshold θ were set as 0 (Onnela, Chakraborti, Kaski, Kertesz, & Kanto, 2003). The dynamic threshold method was used for θ (where θ was assigned different values from 0.1 to 0.9) to extract the important relationships among the stocks in the stock network structures (Moghadam, Mohammadi, Kashani, & Shakeri, 2019; Dimitrios & Vasileios, 2015; Namaki, et al., 2011; Huang, et al., 2009).

Results And Discussion

The findings of the study have been discussed below.

Figure 1 shows that both the returns network and volatility network have the same number of nodes and edges at the threshold level $\theta \geq 0$.





In Figure 2, as the threshold level is increased to $\theta \geq 0.1$, a significant change is seen in the number of relationships (edges) of the returns network and volatility network.

Figure 3 shows the networks at the threshold level $\theta \geq 0.2$.

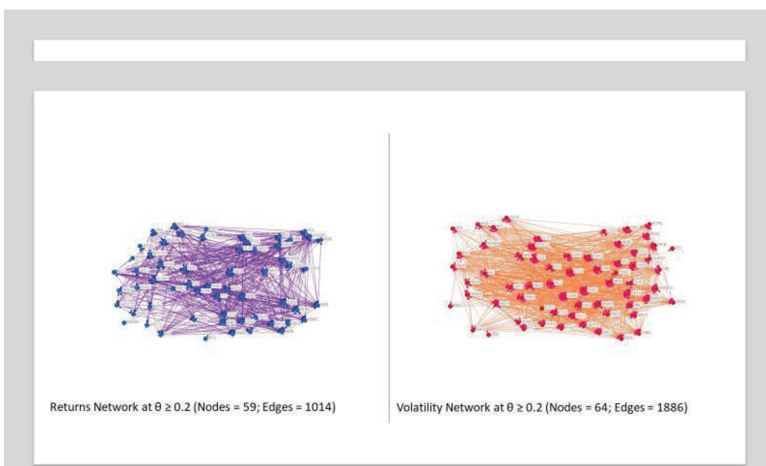
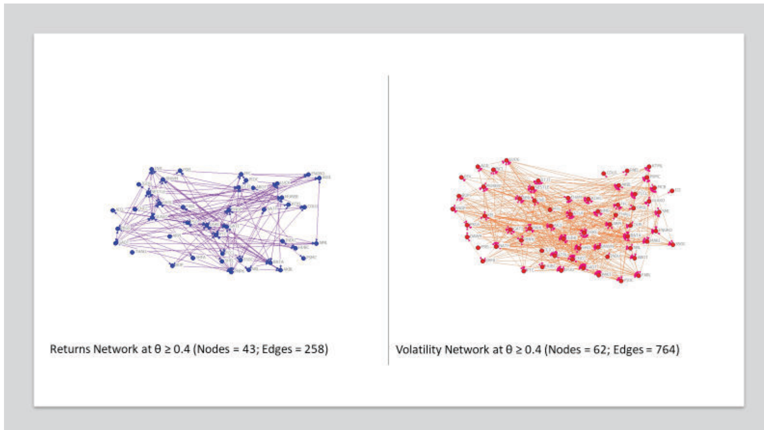
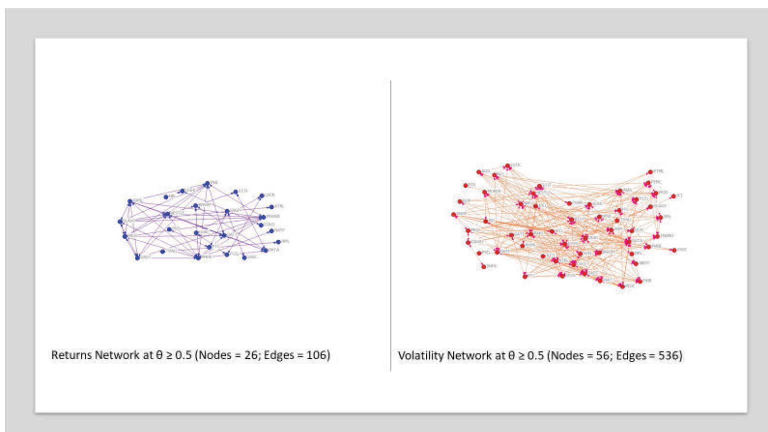


Figure 3

Figure 4 shows that at the threshold level $\theta \geq 0.3$, the returns networks relationships among the stocks had decreased as compared to the volatility network.



In Figure 5 it can be seen that with the increase in the threshold level, the relationships among the stocks are disappearing rapidly.



In Figure 6, another increase in the threshold level shows a great drop in the number of stocks and relationships in the returns network. The volatility network on the other hand, still has a significant number of stocks and relationships at the threshold level $\theta \geq 0.5$.

Returns Network at θ ≥ 0.6 (Nodes = 17; Edges = 60)

Volatility Network at θ ≥ 0.6 (Nodes = 47; Edges = 214)

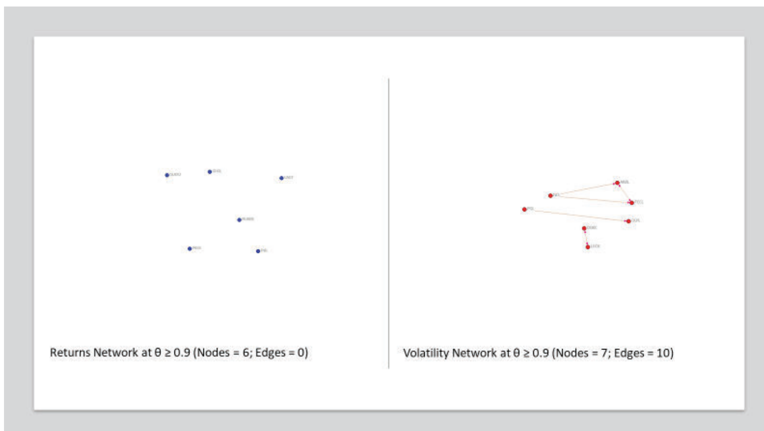
Returns Network at θ ≥ 0.7 (Nodes = 14; Edges = 34)

Volatility Network at θ ≥ 0.7 (Nodes = 31; Edges = 76)

Returns Network at θ ≥ 0.8 (Nodes = 6; Edges = 10)

Volatility Network at θ ≥ 0.8 (Nodes = 19; Edges = 24)

In Figures 7, 8 and 9, it is evident that as the threshold level reaches the higher values of θ, that is 0.6, 0.7 and 0.8, both the returns and volatility networks become sparse and dispersed.
Figure 10 shows that in the volatility network at the threshold level $\theta \geq 0.9$, some relationships still exist among the stocks as compared to returns networks.



Conclusion And Recommendations

This study constructed stock network structures of the stocks listed on the KSE 100 index in the PSX. The nodes of the graphs were stocks and the edges among the stocks were the correlations calculated using the stock returns and stock returns volatility.

The visualization and analysis of the networks for both stock returns and stock returns volatility conclude that volatility is a better and stronger variable as compared to stock returns for the construction of cross-correlation matrices and generation of networks because the volatility networks reveal more useful information in comparison to return networks. As the threshold level was increased, the relationships among the stocks in the returns networks disappeared very rapidly as compared to the volatility networks. More information is lost about the stock network structures with the greater decrease in the relationships of the returns networks.

Therefore, volatility networks provide better information regarding the stock network structures due to the stronger relationships among the stocks. For both returns networks and volatility networks, only a few stocks with relationships were left, implying that the stock network structure of the PSX is a scale-free network. Another important implication observed while analyzing the networks was that only a few stocks had the strongest relationships revealing that the stock market is influenced and controlled by some strong stocks. The results of this study are in line with the previous studies that had studied the stock networks. A study on the network structure of the Greek Stock Market concluded that a small number of strong investors have a large impact on the changes in the stock prices (Dimitrios & Vasileios, 2015). The application of network theory on the US stocks revealed that a very small number of stocks influence the prices of most of the stocks in the market (Tse, et al., 2010).

Further research is needed to explore more techniques of Network Theory that can be used to analyze the stock markets. A comparative analysis of the returns networks and volatility networks in other stock markets of the world is required to confirm the results of this study.

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