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A Complex networks based analysis of jump risk in equity returns: An evidence using intraday movements from Pakistan stock market

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Short running title

Complex Networks and Jump Risk in Pakistan stock market

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A Complex networks based analysis of jump risk in equity returns: An evidence using intraday movements from Pakistan stock market

Abstract

We employ a multi-stage methodology combining complex network analytics and financial risk modelling to unveil the correlation structures amongst the price jump risks of companies forming the KSE-100 index in Pakistan. We identify the most influential companies in terms of jump risk, and identify communities- clusters of companies with similar price movement characteristics or with highly correlated price jumps. We find that equities in Pakistan stock market experience jumps in different time periods that are correlated to varying degrees within and across industries resulting in 19 different communities, four of which are strongly connected. While Oil & Gas, Cement and Banking sectors exhibit a significant representation of firms in communities, the automobile industry, however, seems to play an important role in risk propagation. These results provide an interesting insight to investors and other stakeholders from an emerging market viewpoint identifying the major sectors driving the volatility of KSE-100 index.

Keywords: Complex Network Analysis; Intraday Returns; Realised Jumps; Realised Volatility; Jump Risk
Jel codes : C10; C22; C58; G10

I. Introduction

Modelling stock market volatility and jump risk has gained significant attention in the fields of financial theory and practice. Recent developments in financial modelling and econometrics are focusing on techniques that deal with return and volatility simultaneously. For an investor, a correctly harnessed risk is vital to reduce risk factors and to generate solid returns. Stock price jump risk is one of the relevant phenomena that tend to enhance correlations amongst stocks. Volatility and jump risk are vital for asset allocation, derivative pricing, portfolio development and financial risk management. Since the publication of the seminal paper by Mantegna (1999) on the hierarchical structure of financial markets, several analytical and computational advancements in complex network analysis as well as financial modelling of price volatility and price jump risks have contributed to a better understanding of the stock markets' dynamics. So far, several papers have analysed realised volatility and/or realised jump and correlations among realised price volatility or realised price jumps of stocks listed on developed stock markets such as European and North American stock markets (Karanasos et al. 2020; Kremer, 2017; Hansen et al. 2012; Andersen et al., 2011; Eraker, 2004; Engle 2002), but the literature lacks a study that focuses on realised price jumps of stocks listed on emerging markets like Pakistan whose intraday data is not easily available. This study attempts to fill this void and adopts a non-parametric approach to extract realised jumps in stock prices, reveal correlation structures, and estimate the clustering effects among these realised jumps using a multi-stage methodology combining the fields of financial risk analytics and complex network analytics.

An asset price process experiences infrequent jumps in addition to the continuous Brownian motion and drift movements (Andersen et al., 2007). Jump risk is the sudden and frequent movement of large magnitude in the prices of securities. When there is a rapid substantial change in a stock's price, a jump is said to have occurred. The jump risk often occurs in the presence of an unusual event like the 2008 Financial Crisis; however, it can also be expected during normal periods of financial markets as well. The financial disruptions of US stock market crash (1987), Asian Currency Crisis (1997) and Great Financial Crisis (GFC-2008) had significant effects on security markets around the world and disrupted the functioning of other foreign stock markets. Besides foreign financial markets' linkages, stocks' prices are more prone to the news and signals propagating from the local micro and macro economies as well as the political environment. Many small-scale events of the local environment such as liquidity problems in the market, non-favorable implications of the policies' changes by State Banks and/or Governments, uncertain political environment, and unclear policies and regulations may render jump risk associated with stocks' prices higher in magnitude and frequency. The price jumps generate risks for investors regardless of whether they price risk positively (Driessen and Maenhout, 2013) or negatively (Cremers et al., 2015). The jumps behavior of volatility is quite different from normal and time varying volatility. The modeling frameworks of volatility in the stock market can be classified into two broad categories (Giovannini and Jorion, 1989, Bakshi et al., 1997); namely, time-varying volatility models – ARCH (Engle, 1982) and GARCH (Bollerslev, 1986) type of models, and Jump risk models in which quadratic variation (price process) is considered as a measurement tool for diffusion risk (Merton and Morton, 1980).

Historically, numerous research studies have used daily frequency of stocks' prices to study the jump risk factor despite the inherent limitation that the daily data do not capture the volatility fluctuations throughout a day. However, recent developments in the fields of Computing and Big Data have made it possible to record prices with higher frequencies. The data of intraday level and even on the frequency of a minute's level provide a whole new source of information and inference. By utilising fast computing techniques, recent studies have used these high frequency data to uncover new characteristics, behavior, and other aspects relating to the volatilities of securities. Of high significance are the contributions on volatility modelling by, for example, Andersen and Bollerslev (1998) who decomposed Deutsche Mark-Dollar Volatility into intraday activity patterns, macroeconomic announcements, and volatility persistence (ARCH) known from daily returns, Andersen (2001) who proposed one of the first measures of realised volatility that use intraday data, Barndorff-Nielsen and Shephard (2004) who proposed the bipower variation (BPV) measure and a multipower variation (MPV) measure to estimate integrated variance, and Andersen et al. (2012) who proposed a measure known as MinRV to estimate integrated variance. On the other hand, according to stock network theory, the stocks in the same market are closely linked; thus, they follow identical high or low patterns simultaneously. This underlying behavior in the stock market has been termed as 'stock networks'. With the advancements in computing, several algorithms have been developed to analyse stock networks. In this paper, we propose a multi-stage methodology for analysing price jump risk and its potential contagion effect in the Pakistani stock market, as proxied by the KSE-100 index, over the period ranging from September 12, 2018 to May 31, 2019.

This paper contribution to the literature is manifold. It is the first attempt to analyse the jump risk of stocks forming the Pakistani stock market index KSE-100 using high-frequency data on stock prices. Pakistan's stock market remained a red hot in recent years. In 2017, the KSE index witnessed an impressive surge to 500% since 2009 and left the neighbouring markets in China and India far behind. Since then, the market has been experiencing a turbulent phase. It touched a bottom around 27000 points (i.e., a decline of approximately -48%) in January 2020. In addition, using a multi-stage methodology combining financial risk modelling and complex network analytics, we unveil the correlation structures amongst the price jump risks of companies forming the KSE-100 index, identify the most influential companies jump risk-wise, and identify communities or clusters of companies with similar price movement characteristics or with highly correlated price jumps which are highly likely to experience a chain reaction after an influencer experiences a price jump.

The main findings of this study could be summarised as follows. Stock prices exhibit high volatility in different time periods and realised jump extraction results confirm the presence of jump risk in companies listed under KSE-100 Index. The jump risk is an exigent portion of stock price realised volatility (Chao et al., 2017; Guo et al. 2019). In addition, there are important correlations amongst price jumps of certain companies' stocks, as revealed by the minimum spanning tree (MST) structure of the complex network of stocks forming the KSE-100 Index; thus, stock price jumps in one stock will cause a price jump in neighboring stocks in the MST. Furthermore, nineteen communities of stocks were identified and reveal that, in the Pakistani stock market, two car manufacturers; namely, Pak Suzuki Motors and Indus Motors Company Limited (Toyota), lead the list followed by MCB Bank as the most influential in the MST, whereas companies like K-Electric and Nishat Mills Limited lying at the edge of the complex network have smaller influence; i.e., their price jumps are not correlated with those of other companies. The largest community consists of nine companies viz. UBL, HBL, Meezan Bank, PSO, Hascol, OGDCL, Sui Northern, Indus Motors and Kohat Cement Company Limited; whereas, the smallest community consists of two companies; namely, Engro Fertilizer and Pioneer Cement. Finally, some companies like MCB, Honda Atlas and Fauji Cement are not part of any community. Overall, sectors such as Oil & Gas, Cement, Banking, Engineering, Fertilizer and Automobile have a clearly dominant representation across communities such that Oil & Gas and Cement sectors which are represented in 7 communities, while Banks, Engineering, Fertilisers, and Automobile sector firms are observed in 4 communities each. The firms in the largest community are clustered around four major sectors, including Oil & Gas, Cement, Banking and Automobile sector. The significance of these sectors is apparent from the fact that the combined market capitalization of three sectors only, including Oil & Gas, Cement and Banking sector, is approximated around 15.80 Billion USD which is almost 34% of the total market capitalization of KSE-100 index. These trends may potentially provide a useful insight to investors and other stakeholders of the market, in particular, the sectors driving the market volatility.

The remainder of the paper is organised as follows. Section 2 describes the data and methodology used, section 3 presents the empirical findings while section 4 concludes the paper.

II. Data and Methodology

In this section, we shall provide details on our dataset (section 2.1) and describe our methodology (section 2.2) – see Figure 1 for a snapshot of the design of the methodological framework.

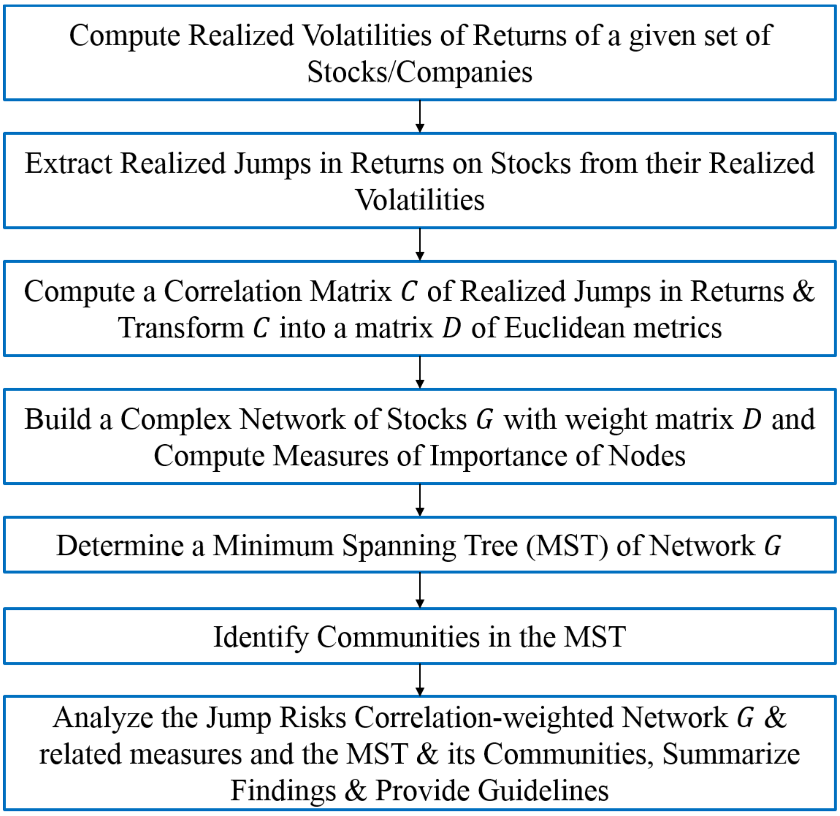

Figure 1: Methodology for analysing jump risk in a stock market

II.1. Data

For analysis purposes, this study uses intraday stock prices of 100 firms listed on Pakistan stock exchange and belong to the KSE-100 Index representing 34 sectors. The data consist of 925,641 transactions recorded from September 12, 2018 to May 31, 2019. Using the high frequency package of R, this transaction data has been categorised into 5-minute frequency and data on stocks with incomplete trading days was discarded. As a result of the cleaning and reorganisation of the initial data, we are left with a dataset of 168 days for 48 companies having 12,415 transactions.

II.2. Methodology

Hereafter, we shall describe in detail the steps of the proposed methodology for analysing jump risk in a stock market.

Step 1: Compute realised volatilities

For each stock i ($i = 1, \ldots, n$) and trading day t ($t = 1, \ldots, T$), first compute its *intraday returns* $r_{i,k}^t$ as follows:

$$r_{i,k}^t = \ln\left(\frac{p_{i,k}^t}{p_{i,k-1}^t}\right), k = 1, \ldots, \tau$$

where $p_{i,k}^t$ denote the kth price of stock i on day t, $p_{i,k-1}^t$ denote the five min lag price on day t, τ denote the number of five-minute intraday return observations in a day t, and T denote the number of trading days in a year. Then, compute the *realised variance* on any day t, say RD_i^t, as follows:

$$RD_i^t = \sum_{k=1}^{\tau} r_{i,k}^{t\,2}, t = 1, \ldots, T.$$

Finally, compute the *realised volatility* on any day t, say RV_i^t, as follows:

$$RV_i^t = \sqrt{T.RD_i^t}, t = 1, \ldots, T.$$

Step 2: Extract realised jumps from realised volatilities

A realised volatility (RV) estimator measures the total quadratic variation of the observed returns process, including the contribution from the cumulative squared jumps. On the other hand, an integrated variance (IV) estimator measures the continuous part of the quadratic variation. Thus, a RV estimator minus an IV estimator provides an estimate of realised jumps. Typical estimators of IV in the presence of jumps include the bipower variation (BPV) measure and multipower variation (MPV) measures (e.g., tripower variation measure, quadpower variation measure, fourth order power variation measure). In this paper, we use instead an estimator proposed by Andersen et al. (2012), known as MinRV, which provides additional robustness to jumps and/or market microstructure noise by using nearest neighbor truncation; that is, the absolute returns are truncated at a level controlled by the neighboring returns. To be more specific, MinRV uses one-sided truncation as each intraday return is compared only to the subsequent absolute return as reflected in its mathematical formulation:

$$MinRV_i^t = \frac{\pi}{\pi-2}\left(\frac{\tau}{\tau-1}\right)\sum_{k=1}^{\tau-1} min\left(\left|r_{i,k}^t\right|, \left|r_{i,k+1}^t\right|\right)^2.$$

In sum, for each stock i ($i = 1, \ldots, n$) and trading day t ($t = 1, \ldots, T$), the *realised jump* of stock i on any day t, say RJ_i^t, is computed as follows:

$$RJ_i^t = RV_i^t - MinRV_i^t.$$

Step 3: Compute realised jumps' correlation matrix C and transform it into an Euclidean distance matrix D

The (i, j)-entry of the realised jumps' correlation matrix, say $C_{n\times n}$, is computed as follows:

$$corr(RJ_i, RJ_j) = \frac{\sum_{t=1}^{T}\left(RJ_i^t - \mu(RJ_i)\right)\left(RJ_j^t - \mu(RJ_j)\right)}{\sqrt{\sum_{t=1}^{T}\left(RJ_i^t - \mu(RJ_i)\right)^2}\sqrt{\sum_{t=1}^{T}\left(RJ_j^t - \mu(RJ_j)\right)^2}},$$

where $\mu(RJ_i) = \sum_{t=1}^{T} RJ_i^t / T$. Since this realised jumps' correlation matrix is intended to be used for building a weighted network of n stocks, say G, in the next step where the weight matrix should satisfy the properties of an Euclidean distance matrix, on one hand, and correlation coefficients could be negative and therefore cannot be used as a distance between stocks, on the other hand, hereafter we shall use a generalised metric defined using as distance an appropriate function of the correlation coefficient. To be more specific, we transform the correlation coefficients $corr(RJ_i, RJ_j)$ into positive real number weights as follows:

$$d(i,j): corr(RJ_i, RJ_j) \in [-1,1] \to \sqrt{2\left(1 - corr(RJ_i, RJ_j)\right)} \in [0,2].$$

We shall denote the distance matrix thus obtained by $D = (d(i,j); i,j = 1, \dots, n)$.

Step 4: Build a network of stocks G with weight matrix D and compute relevant measures to get topological insights

In order to analyse the relationships between the price jumps of n stocks, as measured by the realised jumps computed in step 2, a weighted complete graph $G = (V, E, D)$ is constructed where V denote the set of vertices representing stocks or companies, E denote the set of edges connecting pairs of vertices or stocks, and D is the matrix of weights of edges representing the distances between vertices or equivalently the strengths of the relationships between jump risks of stocks, which are a function of the correlation coefficients. We shall refer to graph G as a realised jumps correlations-weighted network of stocks or simply a complex network.
Then, to get topological insights from complex network G, several measures are available in the social network analysis and complex network analysis literatures. However, for our application, the most relevant measures are vertex-related and belong to the centrality measures category, as the centrality of a vertex measures its potential importance, influence, or prominence in a network based on its relative position compared to other vertices in a network. In our case, influential stocks may influence investors' decisions during extreme events when some stocks or categories of stocks often tend to move together. Amongst centrality measures, betweenness and closeness centralities are especially enlightening the important roles some vertices could play in the network. *Closeness Centrality* of a given vertex i, say $C_C(i)$, is measured by the inverse of the sum of geodesic distances from vertex i to all other vertices in the graph or undirected network, where the geodesic distance between two vertices is the number of edges on the shortest path linking them (Bavelas, 1950) and thus reflects how close vertex i is to all other vertices in the network:

$$C_C(i) = 1/\textstyle\sum_{j \neq i} \#e(\pi_{ij});$$

where $\#e(\pi_{ij})$ denote the number of edges on the shortest path π_{ij} between vertices i and j. Note that $C_C(i) \in [0,1]$. Note also that a vertex or stock i with higher $C_C(i)$ is closer to all other vertices in the network and $C_C(i)$ could be viewed as a measure of the 'speed' with which stock i price jump effect flows or propagates through the network (contagion speed). On the other hand, *Betweenness Centrality* of a given vertex i, say $C_B(i)$, measures how often a vertex appears on the shortest paths between two other vertices in the network (Freeman, 1977) and thus reflects the relative importance of a vertex in linking two other vertices through a shortest path in the network:

$$C_B(i) = \textstyle\sum_{j \neq i} \sum_{k \neq i} \frac{\#\pi_{jk}(i)}{\#\pi_{jk}},$$

where $\#\pi_{jk}$ denote the number of shortest paths between vertices j and k, and $\#\pi_{jk}(i)$ denote the number of shortest paths between vertices j and k that pass through vertex i. Note that $C_B(i)$ is often normalised as follows to obtain a measure that lies within the interval $[0,1]$:

$$\frac{C_B(i) - \min\limits_{j \in V} C_B(j)}{\max\limits_{j \in V} C_B(j) - \min\limits_{j \in V} C_B(j)}.$$

Note also that a vertex or stock i with higher $C_B(i)$ would have wider price jump effect over the network of stocks (contagion spread), as it is directly or indirectly connected to other stocks by lying on a higher proportion of the shortest paths between them.

Step 5: Determine a Minimum Spanning Tree (MST) of complex network G

Trees, in general, and spanning trees, in particular, play an important role in the investigation of the dynamical and topological properties of complex networks. In edge-weighted networks such as complex network $G = (V, E, D)$, a spanning tree of G is a subgraph of G which covers all the vertices of G with the minimum possible number of edges. A minimum spanning tree (MST) of G is a spanning tree of G which has the minimum total weight out of all possible trees that span the entire network G. Note that a spanning tree for a complete graph with n vertices has $n - 1$ edges; thus, any edge belonging to the MST indicates that the jump risks of the corresponding stock prices are connected or relatively highly correlated. As compared to the correlation network, or equivalently the correlation matrix C, the MST provides a skeletal structure with only $n - 1$ edges, and thus attempts to strip the system's complexity down to its essentials (Johnson et al, 2005). As shown by Mantegna (1999), the practical justification for using the MST lies in its ability to provide economically meaningful information. Since the MST contains only a subset of the information from the correlation matrix, in principle it cannot tell us anything which we could not obtain by analysing the matrix C itself. However, it turns out that often it can provide an insight into the system's overall behavior which would not be so readily obtained from the (large) correlation matrix itself. Note that the number of spanning trees for a complete graph with n vertices is n^{n-2}; thus, it would be computationally inefficient to consider all the possible spanning trees to derive the MST. Instead, there are three widely used algorithms for deriving a MST, i.e., Kruskal's algorithm (Kruskal, 1956), Prim's algorithm (Prim, 1957) and Sollin's algorithm (Sollin, 1965). In this paper, we use Prim's algorithm, because our complex network is dense (Jarvis & Whited, 1983). Prim's algorithm builds a MST one vertex at a time, starting from an arbitrary vertex in G, at each step adding the cheapest possible connection from the tree to another vertex not yet in the tree until all vertices are in the tree.

Step 6: Identify communities in the MST

In many applications, complex networks are characterised by a heterogeneous structure (e.g., a heterogeneous distribution of the weights of the edges connecting vertices) which often results in the presence of a so-called community structure, where a network, say $G = (V, E, D)$, exhibits a community structure if and only if its set of vertices V can be divided into two or more (potentially overlapping) subsets – also referred to as clusters – so that the vertices belonging to the same subset or cluster are similar (e.g., densely connected; have strong links; have common features) and those belonging to different subsets or clusters are not (e.g., not connected or sparsely connected; have no links or weak links; do not have much features in common). In practice, the existence of communities in a complex network generally affects various processes such as the spreading of the effect of a specific event over the network; therefore, it is important to find out whether communities exist within correlation network G. In addition, communities often have very different properties compared to the average properties of the network, which might be misleading.

In order to identify communities or clusters in a network; such as our complex network G, a variety of clustering algorithms are available. These algorithms could be classified into one of several categories based on the type of approach they adopt for determining communities: (1) modularity-based approach; e.g., FastGreedy (Clauset et al., 2004), Louvain (Blondel et al., 2008), Leading eigenvector (Newman, 2006) and RenEEL (Guo et al., 2019); (2) node similarity-based approach; e.g., WalkTrap (Pons & Latapy, 2005); (3) compression-based approach; e.g., InfoMap (Rosvall et al., 2007, 2010); (4) significance-based approach; e.g., Order Statistics Local Optimization Method (Lancichinetti et al., 2011); (5) diffusion-based approach; e.g., Label Propagation (Raghavan et al, 2007); and (6) centrality measure-based approach; e.g., Girvan & Newman algorithm (Girvan & Newman, 2002) and Visualization Of Similarities or VOS for clustering (Waltman et al., 2010). In this paper, we choose to use the

VOS for clustering algorithm to uncover communities, because of its attractive design features as outlined below.

The aim of VOS for clustering is to find for each vertex i a positive integer x_i that indicates the cluster or community to which vertex i belongs so that stocks or companies that have a high similarity are located close to each other, whereas companies that have a low similarity are located far from each other. To be more specific, the objective to optimise/minimise is:

$$V(x_1, \dots, x_n) = \sum_{\substack{i<j \\ i,j \in E(MST)}} s_{ij}\delta_{ij}^2 - \sum_{\substack{i<j \\ i,j \in E(MST)}} \delta_{ij}$$

where $E(MST)$ denotes the set of edges in the MST, δ_{ij} is given by

$$\delta_{ij} = \begin{cases} 0 \; if \; x_i = x_j \\ \frac{1}{\gamma} \; if \; x_i \neq x_j \end{cases}$$

the association strength s_{ij} of vertices i and j is given in our case by

$$s_{ij} = d(i,j) = \sqrt{2\left(1 - corr\left(RJ_i, RJ_j\right)\right)},$$

and γ ($\gamma > 0$) is a parameter referred to as the resolution parameter and represents the degree of 'resolution' of analysis. Note that $V(x_1, \dots, x_n)$ can be interpreted in terms of attractive and repulsive forces between vertices, where the first term represents an attractive force and the second term represents a repulsive force. Thus, the overall effect of the two forces is that vertices with a high association strength are pulled towards each other while vertices with a low association strength are pushed away from each other. Note also that, by means of the resolution parameter γ, VOS for clustering can deal with the resolution limit problem (Fortunato & Barthélemy, 2007) experienced by, for example, modularity-based clustering methods which may fail to identify small clusters; in sum, VOS for clustering can always identify small clusters by choosing a sufficiently large value for γ.

Step 7: Analyse the jump risks correlation network G and related measures, its MST and related communities, and summarise findings and provide guidelines. The outcome of this step, including plots of the MST and its communities, is detailed in the next section. Hereafter, we shall describe the VOS method used for mapping entities (e.g., stocks or companies) in a high-dimensional space into a lower-dimensional space for visualisation purposes (van Eck & Waltman, 2007). The aim is to find for each vertex i (i.e., object or entity such as a stock or company) a vector of coordinates $x_i \in R^2$ that indicates the location of vertex i in a 2-dimensional map so that stocks or companies that have a high similarity (i.e., their realised price jumps are highly correlated) are located close to each other, whereas companies that have a low similarity are located far from each other. This is achieved by minimising the following objective function:

$$V(x_1, \dots, x_n) = \sum_{\substack{i<j \\ i,j \in E}} s_{ij}d_{ij}^2 - \sum_{\substack{i<j \\ i,j \in E}} d_{ij}$$

where d_{ij} denotes the distance between vertices i and j and is given by

$$\left\|x_i - x_j\right\| = \sqrt{\sum_{k=1}^{2}\left(x_{ik} - x_{jk}\right)^2}$$

and the association strength s_{ij} of vertices i and j is given by $s_{ij} = \sqrt{2\left(1 - corr\left(RJ_i, RJ_j\right)\right)}$ in our case.

III. Empirical Findings

III.1. *Intraday Return, Realised Volatility and Realised Jump*

In this section, the statistical properties of intraday returns, realised volatility and realised jumps are reported – see Tables 1-3.

As an example, the time series of five-minute intraday returns of OGDCL is plotted in Figure 2 thereby confirming the fluctuations of five-minute returns of the company. The average returns of Pak Suzuki Motors are the highest (0.0050) and those of Millat Tracttors Limited are the lowest (-0.0290). The Indus Motor Company Limited has the highest maximum return value of 113.79 and K-Electric has the lowest maximum value of 0.42 while Mari Petroleum Company Limited has the lowest minimum value of -142.71 and K-Electric has the highest minimum value of -0.39. Furthermore, Mari Petroleum Company Limited has the highest standard deviation value of 4.8263 and K-Electric has a lowest value of 0.0224.

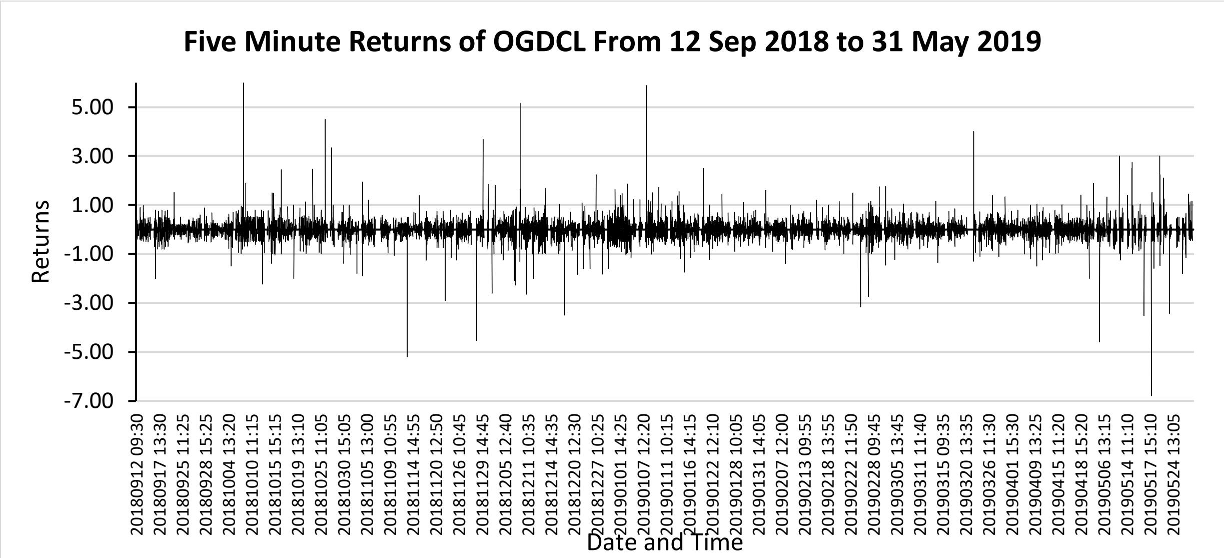

Figure 2: 5-Minute High-Frequency Return of OGDCL

As reported in Table 2, Mari Petroleum Company Limited has the highest average volatility of 296.1223 and K-Electric has the lowest average volatility of 1.4546. Figure 3 shows the intraday volatility of OGDCL and it is clear that there are low and high volatility patterns in five-minute prices.

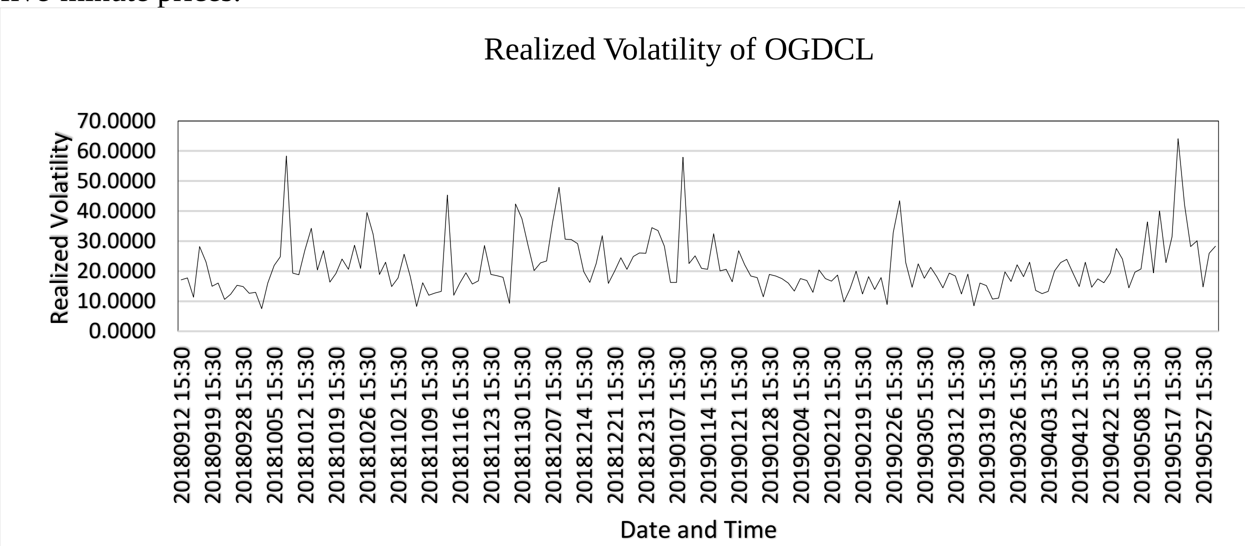

Figure 3: 5-Minute High-Frequency Realised Volatility of OGDCL

The results of realised jumps are different than those of realised volatility. K-Electric has highest average value of 6.2088 and Lucky Cement has lowest average value of 0.1373. Figure 4 shows the movements of 5-minute realised jumps of OGDCL for September 2018 to May 2019. We can observe relatively large price jumps in September 2018, November 2018 and

March 2019. Also, there have been relatively smaller jumps during the specified period indicating that the market is not stable. However, despite some companies showing little jumps, overall the KSE-100 Index exhibits realised jumps.

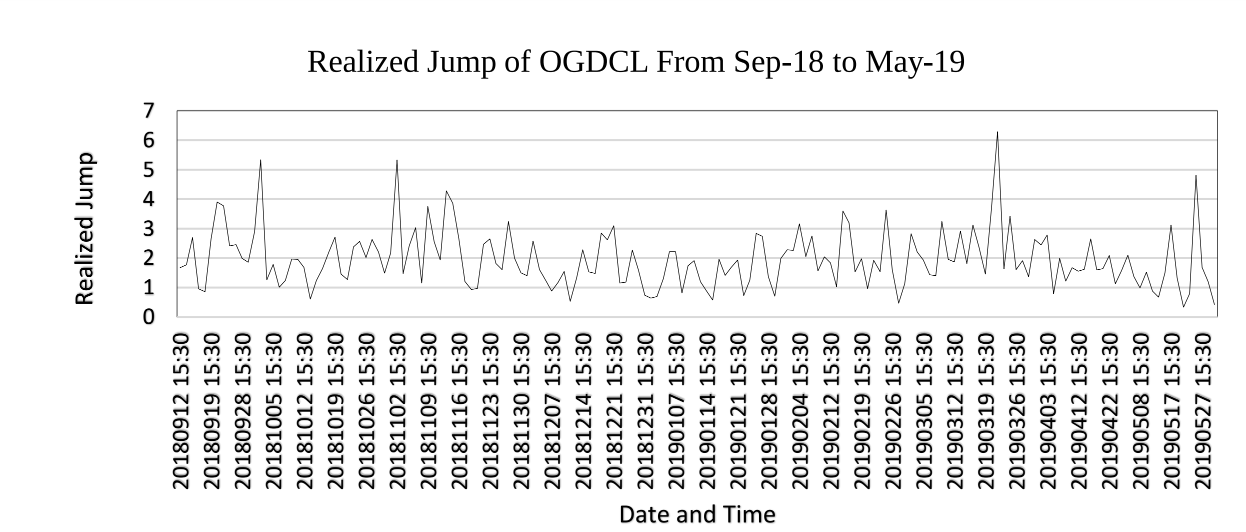

Figure 4: 5-Minute High-Frequency Realised Jumps of OGDCL

Table 1: Summary statistics of intraday returns

Name	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis
OGDCL	-6.8000	6.0000	-0.0012	0.3328	0.1703	63.2265
Pak Electron	-1.4200	2.4600	-0.0009	0.1173	1.3469	42.3962
Pak Intl Bulk	-0.9500	0.7700	-0.0003	0.0407	-0.1052	84.1025
Pak Petroleum	-31.0000	8.5000	-0.0033	0.5690	-13.8479	762.6454
PSO	-57.5500	16.9100	-0.0113	0.8968	-20.8632	1423.1459
Pak Suzuki Motors	-28.4700	69.1000	0.0050	1.2567	14.4892	847.7936
Pioneer Cement	-4.3700	2.7500	-0.0012	0.1891	-0.3138	57.9612
Searle Co.	-40.3000	24.8900	-0.0129	1.0392	-3.5934	243.9521
Sui Northern	-7.0100	4.9000	-0.0017	0.2954	0.3055	64.5452
Sui Southern	-1.2600	1.1500	-0.0007	0.0883	0.4903	26.2244
TRG	-1.8900	1.4400	-0.0011	0.1076	-0.1680	38.3230
UBL	-8.5000	8.0000	0.0000	0.4617	0.6488	59.4464
Attock Refinery	-41.7800	8.1800	-0.0094	0.7069	-16.5335	1014.2831
BOP	-0.7400	1.0600	0.0000	0.0425	2.0707	73.9961
D.G Khan Cement	-6.3900	5.2400	-0.0034	0.3520	0.1763	53.6942
Engro Corporation	-42.3900	15.0400	-0.0024	0.8645	-9.4626	517.1596
Engro Fertiilizer	-4.5000	3.2400	-0.0006	0.1761	-1.2737	88.4767
Fauji Cement	-1.3000	1.6400	-0.0006	0.0810	1.0516	54.0435
Hascol	-57.5100	16.1000	-0.0163	0.8188	-27.2766	2017.0507
HBL	-8.5000	6.9000	-0.0019	0.4293	0.1035	44.7779
Honda Atlas	-17.2800	24.7800	-0.0086	1.0835	1.3825	65.2114
Hub	-4.9600	4.4200	-0.0008	0.2485	-0.8085	53.8627
Int Steel	-4.2500	4.5700	-0.0046	0.2938	0.2278	43.4500
K-Electric	-0.3900	0.4200	-0.0001	0.0224	0.7039	38.5579
Lucky Cement	-26.7500	25.2100	-0.0064	1.4583	0.7683	61.9339
Maple Leaf	-2.6000	3.0000	-0.0022	0.1842	0.5481	40.9384
MCB	-5.3900	9.4500	-0.0017	0.4955	1.8567	42.8404
Nishat Chunian Ltd.	-3.0500	2.8300	-0.0010	0.1791	0.0707	38.9482
Fauji Fertilizer Co. Ltd.	-5.3600	8.8800	-0.0002	0.2377	4.3528	238.4424
Cherat Cement Co. Ltd.	-5.0000	3.4600	-0.0036	0.2926	-0.3325	40.2005
Amreli Steels Ltd.	-5.0000	3.4600	-0.0036	0.2926	-0.3325	40.2005

Kot Addu Power Co. Ltd.	-6.9000	2.9500	-0.0015	0.1422	-8.8494	504.2026
National Refinery Ltd.	-14.6400	15.4800	-0.0164	1.0146	-0.1710	50.5923
Nishat Mills Ltd.	-7.5700	7.4400	-0.0024	0.4480	0.1146	39.0190
Engro Foods Ltd.	-4.3200	4.8200	-0.0025	0.2849	1.0846	42.4441
International Industries Ltd.	-12.5000	10.6400	-0.0092	0.6775	-0.1339	55.1710
Bank Alfalah Ltd.	-6.0000	3.9500	-0.0007	0.1791	-2.5997	170.1191
Millat Tractors Ltd.	-54.0000	49.0000	-0.0289	3.0571	0.4841	62.0841
PakistanTelecommunication Co. Ltd.	-0.4400	0.5700	-0.0002	0.0338	1.1324	40.7750
Kohat Cement Co. Ltd.	-29.3500	5.1100	-0.0051	0.4767	-18.7483	1187.1048
Mari Petroleum Co. Ltd.	-142.7100	85.0000	-0.0286	4.8263	-1.8641	126.2316
Indus Motor Co. Ltd.	-79.9000	113.7900	-0.0274	4.2531	1.2027	96.5239
Attock Cement Pakistan Ltd.	-27.3800	5.8200	-0.0049	0.4978	-13.6641	772.7361
Meezan Bank Ltd	-10.2500	5.0000	-0.0002	0.3614	-2.7277	126.3173
GlaxoSmithKline	-7.0000	8.0000	-0.0039	0.5275	0.8737	48.3580
Pak Oil Field	-137.7300	15.9800	-0.0163	1.7205	-42.7235	3370.6095
NBP	-2.1200	2.6500	-0.0008	0.1381	1.4138	45.5724
Fauji Fertilizer Bin Qasim Ltd.	-2.2500	1.8100	-0.0017	0.1328	0.3523	41.6291

Table 2: Summary statistics of realised volatility

Name	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis
OGDCL	7.5189	64.0898	21.5646	9.3152	1.7895	4.5059
Pak Electron	2.5569	20.9853	7.6954	3.4008	1.2042	1.9015
Pak Intl Bulk	0.0000	8.2661	2.1586	1.9702	0.4694	-0.4173
Pak petroleum	6.3645	267.2986	33.6752	22.8536	6.8809	66.1361
PSO	0.0000	490.1062	48.6475	40.6914	7.9795	83.5674
Pak Suzuki Motors	0.0000	186.5191	39.0333	49.2723	0.8732	-0.4701
Pioneer Cement	2.5863	38.5880	12.5166	5.1973	1.7024	5.0610
Searle Co.	0.0000	345.1306	63.4883	37.5463	3.3214	19.8240
Sui Northern	6.0887	62.8047	19.5993	7.9769	1.6629	4.9158
Sui Southern	2.1281	12.0246	5.9630	1.9331	0.8426	0.7013
TRG	2.1483	17.0189	7.0812	3.0037	1.0884	1.0997
UBL	4.3283	83.3479	29.7971	13.8445	1.2978	1.7486
Attock Refinery	0.0000	357.6248	39.7951	31.5557	6.3640	61.3961
BOP	0.6350	9.3972	2.6728	1.3917	1.8741	4.7431
D.G Khan Cement	7.0228	64.3482	22.8257	10.7227	1.1438	1.2445
Engro Corporation	8.9623	363.2156	51.2348	33.7684	5.2336	43.4853
Engro Fertiilizer	3.3973	38.8728	11.3941	5.4109	1.9866	5.5986
Fauji Cement	0.4948	14.3770	5.3071	2.3403	1.3060	2.0055
Hascol	6.6131	491.5666	41.8148	41.2238	8.0994	85.4619
HBL	5.2479	73.5384	28.3411	11.4688	1.4863	3.4538
Honda Atlas	0.0000	210.2653	69.9284	32.5587	1.3582	3.8008
Hub	0.0000	44.7155	16.0604	7.2794	1.3746	3.0703
Int Steel	0.0000	50.3045	19.2743	8.4772	1.0495	1.2659
K-Electric	0.0000	3.5425	1.4546	0.5532	1.3234	2.9260
Lucky Cement	11.4915	253.6916	94.7199	44.3599	1.1292	1.1588
Maple Leaf	3.9363	30.7444	12.0727	5.1797	1.1180	1.1956
MCB	6.0000	75.0772	31.5525	14.0840	1.0815	0.7672
Nishat Chunian Ltd.	0.0000	38.7002	11.6586	5.0931	1.4153	4.7344
Fauji Fertilizer Co. Ltd.	4.1500	76.6961	14.3618	9.2660	2.7893	12.6964
Cherat Cement Co. Ltd.	4.5513	48.8614	19.2535	8.2016	1.0318	1.4604
Amreli Steels Ltd.	4.5513	48.8614	19.2535	8.2016	1.0318	1.4604

Kot Addu Power Co. Ltd.	0.0000	59.1225	8.2474	5.7212	4.7558	37.4103
National Refinery Ltd.	0.0000	218.0695	64.4356	32.4171	1.1147	2.5849
Nishat Mills Ltd.	0.0000	99.5442	29.1603	13.1250	1.6407	5.2101
Engro Foods Ltd.	6.4844	44.7914	19.0026	7.2341	0.9898	0.9838
International Industries Ltd.	0.0000	138.6933	42.9355	22.5155	1.4595	3.3168
Bank Alfalah Ltd.	0.0849	52.5482	11.1473	6.3377	2.5566	12.2749
Millat Tractors Ltd.	0.0000	612.5535	185.6056	112.1323	1.1459	1.1214
Pakistan Telecommunication Co. Ltd.	0.4243	5.2725	2.1550	1.0093	0.9775	0.6924
Kohat Cement Co. Ltd.	0.0000	250.7116	26.8902	20.8481	7.5878	79.7757
Mari Petroleum Co. Ltd.	0.0000	1414.5538	296.1223	179.7830	2.2030	9.3791
Indus Motor Co. Ltd.	0.0000	965.5402	254.4105	164.6525	1.1319	1.9624
Attock Cement Pakistan Ltd.	3.7470	237.0212	28.9123	21.1460	6.0042	55.9476
Meezan Bank Ltd	0.0000	86.9950	21.0920	13.7257	1.6343	4.8023
GlaxoSmithKline	0.0000	84.2243	32.9246	17.1639	0.6958	0.3739
Pak oil Field	21.9012	1174.7470	81.7760	92.1508	10.2004	119.9952
NBP	3.5527	33.6817	8.7983	4.2075	1.9921	7.4736
Fauji Fertilizer Bin Qasim Ltd.	1.2728	20.8526	8.6670	3.7644	0.8491	0.7461

Table 3: Summary statistics of realised jumps

Name	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**	**Skewness**	**Kurtosis**
OGDCL	0.3359	6.2912	1.9585	0.9788	1.3131	2.8710
Pak Electron	1.4684	6.2963	5.0627	1.2838	-1.2763	0.5580
Pak intl bulk	3.1324	6.2972	6.0242	0.4372	-4.8808	26.0110
Pak petroleum	-0.1045	3.0198	1.0512	0.5249	0.5975	0.4746
PSO	0.0099	3.4733	0.6969	0.4728	1.9517	7.4265
Pak Suzuki Motors	-0.2816	1.4951	0.2921	0.4138	1.0820	0.8564
Pioneer Cement	0.6229	6.2334	3.1088	1.3330	0.5976	-0.1487
Searle Co.	-0.2547	6.2539	0.4973	0.6033	6.0732	53.5837
Sui Northern	0.4013	6.3064	2.1620	1.0977	1.2206	2.2121
SUI Southern	2.0133	6.2968	5.3097	1.1241	-1.2506	0.4235
TRG	1.7978	6.2940	5.0571	1.2821	-1.0236	-0.3986
UBL	0.0056	6.3067	1.2097	0.7437	2.4595	12.9211
Attock Refinery	-0.0586	4.1163	0.9943	0.6819	1.2439	3.0289
BOP	3.7313	6.2997	6.0856	0.3460	-4.9946	26.9990
D.G Khan Cement	0.2759	6.3068	1.8440	1.0655	1.1255	1.7436
Engro Corporation	-0.0803	1.7535	0.5432	0.3653	0.8325	0.8567
Engro Fertiilizer	0.6665	6.3064	3.3527	1.4217	0.5171	-0.4172
Fauji Cement	1.6974	6.3036	5.7082	0.7983	-2.5843	6.7317
Hascol	0.0281	6.3069	1.1674	1.1809	2.9959	9.9778
HBL	0.0273	3.2180	1.1884	0.5882	0.6603	0.7349
Honda Atlas	-0.1410	3.7034	0.4606	0.4833	2.6227	13.0837
Hub	0.4942	6.3057	2.2438	1.3148	1.4699	2.1543
Int Steel	0.3562	6.3066	2.0353	1.1068	1.4562	3.0534
K-Electric	4.8897	6.3026	6.2088	0.1090	-10.8025	131.0926
Lucky Cement	-0.3673	0.8566	0.1373	0.2388	0.6181	0.3414
Maple Leaf	0.4511	6.2910	3.5982	1.4384	0.0612	-0.9125
MCB	-0.0584	4.6112	1.0086	0.6811	1.9775	7.0393
Nishat Chunian Ltd.	0.5401	6.3068	3.3158	1.4225	0.4498	-0.3993
Fauji Fertilizer Co. Ltd.	0.4338	6.3065	2.9184	1.6243	0.8346	-0.1984
Cherat Cement Co. Ltd.	0.2852	6.3063	2.0125	1.2707	1.9490	4.0001

Amreli Steels Ltd.	0.2852	6.3063	2.0125	1.2707	1.9490	4.0001
Kot Addu Power Co. Ltd.	0.4816	6.3056	4.2115	1.6465	-0.3107	-1.0460
National Refinery Ltd.	-0.1177	6.3070	0.6391	1.0914	4.2239	18.9127
Nishat Mills Ltd.	0.0758	6.3069	1.4529	1.1907	2.3546	6.5708
Engro Foods Ltd.	0.2870	6.3069	2.1837	1.4721	1.5174	1.7518
International Industries Ltd.	-0.0479	6.3070	1.0391	1.2549	3.2367	10.8714
Bank Alfalah Ltd.	0.6495	6.3070	3.8039	1.7311	0.1651	-1.2174
Millat Tractors Ltd.	-0.3448	6.3070	0.2669	0.8795	6.2715	41.1527
Pakistan Telecommunication Co. Ltd.	2.4688	6.3063	6.1559	0.4678	-5.8714	36.8124
Kohat Cement Co. Ltd.	0.1610	6.3069	1.7861	1.6895	1.7774	2.2337
Mari Petroleum Co. Ltd.	-0.2324	6.3071	0.4171	1.4454	3.7087	12.5007
Indus Motor Co. Ltd.	-0.3077	6.3071	0.2784	1.1494	4.7682	22.3442
Attock Cement Pakistan Ltd.	-0.0173	6.3070	1.6464	1.6225	1.9175	2.9327
Meezan Bank Ltd	0.0752	6.3070	2.2926	1.9362	1.1887	0.0495
GlaxoSmithKline	-0.0280	6.3067	1.5357	1.6529	1.8675	2.5780
Pak oil field	-0.3019	1.6704	0.3232	0.3039	1.3038	3.7328
NBP	0.3157	6.3058	4.1779	1.7443	-0.3034	-1.1782
Fauji Fertilizer Bin Qasim Ltd.	0.4432	6.3068	4.1974	1.6667	-0.2377	-0.9462

III.2. Complex Network

Recall that, by design, a shorter (respectively, larger) distance between two vertices of our complex network $G = (V, E, D)$ represents a stronger (respectively, weaker) correlation among their prices' jumps. Different centrality metrics have been computed to identify 'influential' nodes in network G. The complete list of stocks along with their industries, communities, betweenness centrality and closeness centrality is provided in Table 4.

With regards to the clustering of industries into communities, we observe a mixed pattern but with a clearly dominant representation of sectors including Oil & Gas, Cement, Banking, Engineering, Fertilizer and Automobile manufacturers among the communities formed. Out of the nineteen communities formed, four major communities consist of 4 or higher number of firms, while community 2 is the largest one with 9 firms from four major sectors including Oil & Gas, Cement, Banking and Automobile. It is also apparent from these statistics that Oil & Gas has the highest number of total firms (10 firms) present across all the communities, respectively, followed by Cement sector (8 firms) and banking sector (7 firms), while the Oil & Gas sector and Cement sector with their presence in 7 communities each leads in terms of representation in the number of communities, followed by Banks, Engineering, Fertilisers, and Automobile manufacturers present in 4 communities each. It is equally worth noting that these sectors are major market movers. For instance, the combined market capitalisation of three sectors only, including Oil & Gas, Cement and Banking sector, is approximated around 15.80 Billion USD, which is almost 34% of the total market capitalisation of KSE-100 index.

With respect to betweenness centrality, the two leading car manufacturers of Pakistan, Pak Suzuki Motors and Indus Motors Company Limited (Toyota), lead the list followed by MCB Bank. On the other hand, with respect to closeness centrality, Pak Suzuki Motors, Indus Motors Company Limited (Toyota) and MCB Bank lead the list.

Table 4: Complex Network Betweenness and Closeness results

Name	Industry	Community	Betweenness	Closeness
BOP	Commercial Banks	1	0.0000	0.1703
Cherat Cement Co. Ltd.	Cement	1	0.0000	0.1703
Amreli Steels Ltd.	Engineering	1	0.0000	0.1703
Bank Alfalah Ltd.	Commercial Banks	1	0.0000	0.1703
Mari Petroleum Co. Ltd.	Oil & Gas	1	0.2414	0.2043
Attock Cement Pakistan Ltd.	Cement	1	0.0000	0.1703
Fauji Fertilizer Bin Qasim	Fertilizer	1	0.0000	0.1703
OGDCL	Oil & Gas	2	0.0000	0.2554
PSO	Oil & Gas	2	0.0000	0.2554
Sui Northern	Oil & Gas	2	0.0000	0.2554
UBL	Commercial Banks	2	0.0000	0.2554
Hascol	Oil & Gas	2	0.0000	0.2554
HBL	Commercial Banks	2	0.0000	0.2554
Kohat Cement Co. Ltd.	Cement	2	0.0000	0.2554
Indus Motor Co. Ltd.	Automobile Manufacturing	2	0.5828	0.3406
Meezan Bank Ltd	Commercial Banks	2	0.0000	0.2554
Fauji Fertilizer Co. Ltd.	Fertilizer	3	0.0000	0.2260
Kot Addu Power Co. Ltd.	Power Generation & Distribution	3	0.0000	0.2260
National Refinery Ltd.	Oil & Gas	3	0.0842	0.2901
Hub	Power Generation & Distribution	4	0.0842	0.2327
K-Electric	Power Generation & Distribution	4	0.0000	0.1895
Engro Foods Ltd.	Dairy	4	0.0000	0.1895
GlaxoSmithKline	Pharmaceuticals	4	0.1221	0.2938
Searle Co.	Pharmaceuticals	5	0.0426	0.2866
SUI Southern	Oil & Gas	5	0.0000	0.2238
Engro Corporation	Fertilizer	6	0.0000	0.2238
Pakistan Telecom Co. Ltd.	Technology & Communication	6	0.0426	0.2866
Pak Electron	Engineering	7	0.0833	0.2901
Nishat Mills Ltd.	Textile	7	0.0000	0.1865
Millat Tractors Ltd.	Automobile Manufacturing	7	0.0426	0.2282
Pak Suzuki Motors	Automobile Manufacturing	8	0.8104	0.3917
Nishat Chunian Ltd.	Textile	8	0.0000	0.2831
Pak oil field	Oil & Gas	8	0.0000	0.2831
NBP	Commercial Banks	8	0.0000	0.2831
Pak intl bulk	Transport	9	0.0000	0.1942
TRG	Technology & Communication	9	0.3164	0.2831
International Industries Ltd.	Engineering	9	0.2951	0.2398
Pioneer Cement	Cement	10	0.0426	0.2866
Engro Fertiilizer	Fertilizer	10	0.0000	0.2238

Pak petroleum	Oil & Gas	11	0.0000	0.2831
Attock Refinery	Oil & Gas	12	0.0000	0.2831
D.G Khan Cement	Cement	13	0.0000	0.2831
Fauji Cement	Cement	14	0.0000	0.2831
Honda Atlas	Automobile Manufacturing	15	0.0000	0.2831
Int Steel	Engineering	16	0.0000	0.2831
Lucky Cement	Cement	17	0.0000	0.2831
Maple Leaf	Cement	18	0.0000	0.2831
MCB	Commercial Banks	19	0.4921	0.3672

A minimum spanning tree (MST) of complex network G is depicted in Figure 5. The vertices in the center have a stronger influence while the vertices lying at the edge of the tree have lesser influence. When the price of stronger influence vertices jumps, there are lots of jumps in the stock price associated with them, whereas when the price of weaker influence vertices jumps, the stock's price jumps are not substantial.

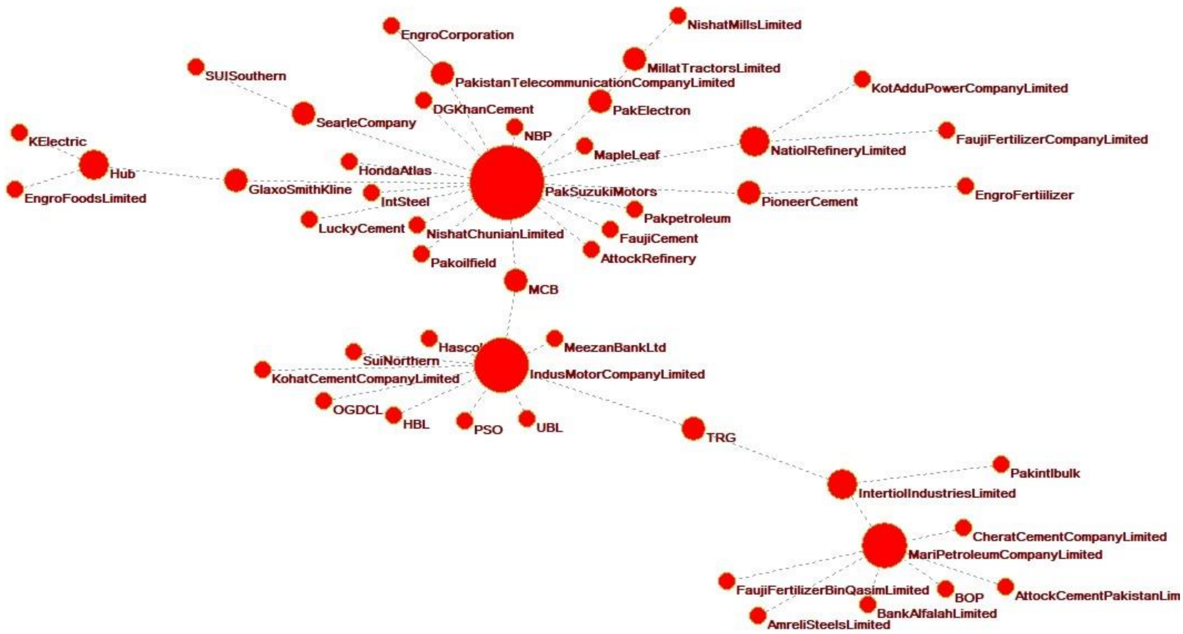

Figure 5: Realized Jumps Correlation Minimum Spanning Tree. Size represent the importance of the node in the MST

Finally, another important topological feature of complex network G being studied is the presence of communities. Vertices that are densely connected tend to be in the same community. The outcome is provided in Figure 6, which shows nineteen different clusters in the sample network with four major communities having four or more companies. The largest community is made up of nine companies including United Bank Ltd., Habib Bank Ltd., Meezan Bank, Pakistan State Oil, Hascol Oil, Oil and Gas Development Co. Ltd., Sui Northern Gas Ltd., Toyota Indus Motors, and Kohat Cement. The results reveal that jump correlation between these companies is high; i.e., a positive jump brings about a positive change in these connected companies. This potentially helps investors precisely forecast the firm-specific jumps to factor this in their investment and risk management strategies. More precisely, volatility jumps are indicative of strong correlations among stocks in the same community. Therefore, fluctuations in the prices of such stocks will cause the price of other stocks to fluctuate. The investor can manage the financial risk in light of the chain reaction within the same community.

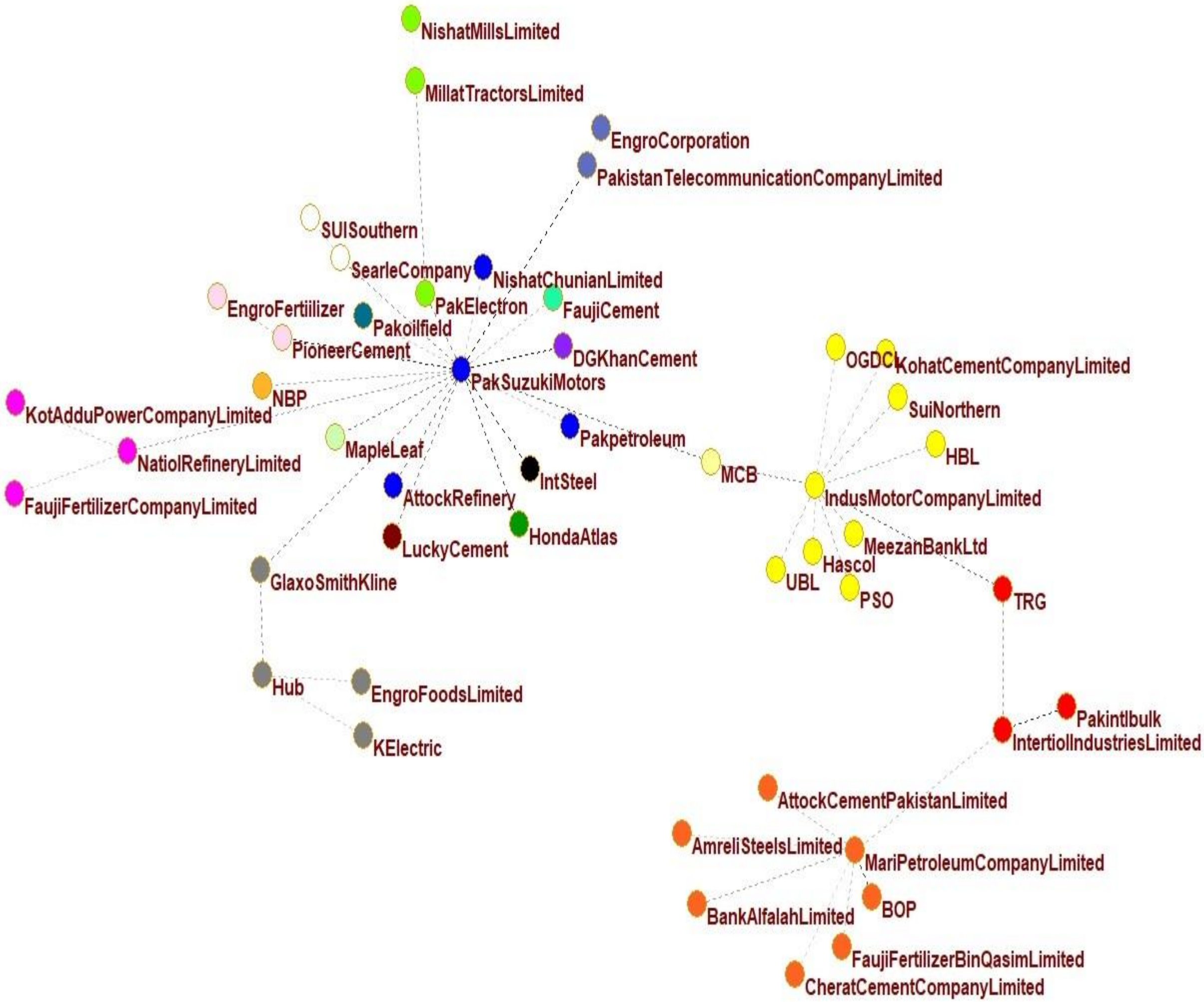

Figure 6: VOS Community Division Diagram

IV. Conclusions and Recommendations

In this study, a complex network of intraday KSE-100 index stocks, weighted by jump risk correlations, was built using intraday five-minute high-frequency stock price data from September 12, 2018 to May 31, 2019, and its vertices or stocks analysed by means of centrality measures. Analysis of vertices with the highest betweenness centrality as well as the highest closeness centrality suggest that the two leading car manufacturers of Pakistan (i.e. Pak Suzuki and Indus Motors-Toyota) along with MCB Bank lead the list. Then, a minimum spanning tree (MST) was determined using Prim's algorithm. The connected vertices (companies or their stocks) in the MST shows that a stock price jump in one stock will cause price jumps in other stocks, which are either directly or indirectly connected to it. Finally, the communities within the MST were identified using the VOS algorithm. The results suggest that the largest community is made up of nine companies including United Bank Ltd., Habib Bank Ltd., Meezan Bank, Pakistan State Oil, Hascol Petroleum Limited, Oil and Gas Development Co. Ltd., Sui Northern Gas Ltd., Toyota Indus Motors, and Kohat Cement. These results confirm that the car manufacturing industry is at the core of the whole industry. We suggest that the development of the manufacturing industry would be vital to reduce the jump risk of the stock market of Pakistan. This study provides insight to investors about idiosyncratic jumps in the stocks and the correlations among jumps in a bid to better formulate their portfolio investment and risk management strategies.

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