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Research Article

# Analysis of Correlation based Threshold Networks of Dow Jones stocks of USA: An Econophysics Approach

**Sushil Kumar[1], Satyam kumar[1], Upender Kumar[2], Sunil Kumar[3], Pawan Kumar[4], and Narinder Verma[5]**

*[1]Department of Physics, Hansraj College, University of Delhi, Delhi-110007, India.*
*[2]Department of Applied Sciences, IIIT Allahabad, Jhalwa, Prayagraj, India*
*[3]Department of Physics, Ramjas College, University of Delhi, Delhi-110007, India.*
*[4]School of Basic and Applied Sciences, K R Mangalam University, Haryana-122103, India.*
*[5]Faculty of Management Sciences and Library Arts, Shoolini University, Solan, H.P. 173229, India*

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***Abstract***

We have investigated the time series of constituents of the Dow Jones Industrial Average (DJIA) for a period of 18 years (2000-2018). DJIA is a dominant stock market index comprising of thirty US based companies. We have applied the Random Matrix Theory (RMT), complex network analysis and hierarchical clustering techniques to extract out the information from the time series of DJIA stocks. The impact of sub-prime crisis of 2008(FC08) on structure and dynamics of network of DJIA stocks is studied by diving the periods under consideration into three distinct periods; pre crisis (PRC), during crisis (DUC) and post crisis (POC) on the basis of volatility. The RMT analysis shows that data analyzed contain important information. Network analysis reveals high correlation among the stocks in the DUC period. The MST and hierarchical clustering techniques support the results of RMT analysis. Degree centralities, closeness centralities and clustering coefficients of DJIA networks increases in DUC period. High correlation and closeness among stocks in DUC period is depicted in various analyses. The dynamic analysis is also carried out which detect various extreme events such as Covid-19. In conclusion, investigation shows that during the period of crisis, there are significant changes in the structure and dynamics of DJIA network. The findings of investigation can be utilized as risk indicator and detection of such crises in future.

*Keywords:* Dow jones, Financial crisis, Covid-19, Network analysis and centralities measures.

## 1. Introduction

The networks of financial indices are widely used in financial analysis and in academia nowadays. In Econophysics [1] many techniques have been used to examine the correlation among stocks [2, 3]. Random Matrix Theory (RMT), complex network analysis, Minimum Spanning Tree (MST) and dendrogram are widely used methods in study of financial networks and their topological properties [4-15]. In the beginning RMT was applied in the nuclear physics to study the energy distribution [4, 8]. Later it has been applied in economics and finance for the portfolio management [9–14]. RMT was introduced for sorting genuine correlations among financial indices [16]. At the time of crises and booms in the market some peaks are observed in the Largest Eigen Value (LEV) [17]. The relationship among different stock markets is investigated by Song et al. [18] and Kenett et al. [19]. Song et al. [18] categorized the stock market dynamics into slow and fast dynamics. The former was connected with globalization, while later was connected with critical events. Sandoval Junior and De Paula Franca [20] have constructed a matrix using correlations among the stocks. Kumar and Deo [21] have studied the correlation among several financial indices using techniques of RMT and network analysis. They have found an increase in correlation among stocks during the period of crisis. Zheng et al. [22] have found that variations in correlations are associated with the occurrence of financial crisis and systemic risk. Kim and Jeong [23] have filtered the correlation matrices of stock returns and identified the multiple stock groups. They have explained how this approach is better than eigenvector approach in reducing the ambiguities. Kim and Jeong [24] have found that spanning trees and networks were strongly correlated.

The financial markets can be denoted by a network where nodes are the financial indices and correlations among their returns are the edges connecting nodes [25-29]. The networks of financial indices are first constructed by Mantegna [25] based on correlation in prices. He proposed the use of correlation based financial networks to analyse time series of DJIA and S&P 500. Onnela et al. [27] have constructed the networks of New York stock exchange (NYSE) and examined the topology of the market.Tumminello et al. [28] have refined Mantegna approach of correlation based financial networks and studied the topological properties of 300 stocks of NYSE using planar maximally filtered graphs (PMFG) technique. Jung et al.[29] investigated the Korean stock market using MST and observed no cluster formation. Huang et al. [30] investigated the topology of stock market of the China. Yook et al.[31] constructed networks of biological, ecological, and economic systems. They have assigned the weightage to the nodes whose strength varies as the network evolves and found the scaling character of distribution of connections.

*E-mail address: sushil8207@gmail.com
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Kim et al. [32] have applied path finding techniques to the Albert and Barabasi Network model. They have shown small world behaviour of network by introducing the concept of generalised diameter. Barabasi et al. [33] have analysed the network of world-wide web (www) and found that network has many universal scale-free characteristics. Kumar et al. [34-37] have studied the stability of stock markets using different techniques.

The aim of present work is to explore the structure and dynamics of DJIA stocks in the vicinity of extreme events such as financial crisis of 2008(**FC08**) and covid-19. DJIA consists of 30 US based companies and this index provides information related to the US stock market.

The organization of paper is as follows: the data analyzed and filtration method used is discussed in section-2. The methodologies used such as RMT, Threshold Network (TN) and hierarchical clustering are explained in the section-3. In section-4, the different centralities measures of the networks are discussed. In section-5 & 6, the outcomes and conclusions from the findings of the investigation are elaborated.

The time series of 28 DJIA stocks (details are listed in Table-1) from 2000 to 2018 is examined. The data was obtained from the Lal Bahadur Shastri Institute of Management, New Delhi. Fig.1a shows the closing prices of the DJIA stocks from Jan, 2000 to Sept, 2018. The major fall in the prices of all stocks can be seen during the crisis period (shown by red ellipse in Fig.1). The daily data of the DJIA stocks is filtered in the similar way as done by Lynall et al. [38]. The FC08 erupted in the United States. It was one of the worst economic crises. To examine the impact of FC08 on the DJIA stocks, three different periods are considered as: PRC, DUC and POC on the basis of volatility (a measure of market fluctuations). The period from 7/6/2006 to 30/11/2007 is taken as 'pre-crisis(PRC)', period from 3/12/2007 to 30/6/2009 as 'during crisis(DUC)' and period 1/1/2010 to 30/6/2011 as 'post-crisis(POC)' [21].

The Fig.2 represents the volatility of individual stock in different period of crisis. A significant increase in the volatilities of all stocks in DUC period can be seen in the Fig.3.

## 2. Data description and filtration

**Table 1.** List of stocks listed in the Dow Jones Industrial Index (DJIA)

| S.No. | Symbol | Company | Industry |
|---|---|---|---|
| 1 | AAPL | Apple | IT |
| 2 | CSCO | Cisco Systems | IT |
| 3 | IBM | IBM | IT |
| 4 | INTC | Intel | IT |
| 5 | MSFT | Microsoft | IT |
| 6 | JPM | American Express | FS |
| 7 | AXP | JPMorgan Chase | FS |
| 8 | GS | Goldman Sachs | FS |
| 9 | JNJ | Johnson & Johnson | PHM |
| 10 | MRK | Merck & Company | PHM |
| 11 | PFE | Pfizer | PHM |
| 12 | CVX | Chevron | Oil & gas |
| 13 | XOM | Exxon Mobil | Oil & gas |
| 14 | HD | The Home Depot | Retail |
| 15 | WMT | Walmart | Retail |
| 16 | KO | Coca-Cola | Food |
| 17 | MCD | McDonald's | Food |
| 18 | MMM | 3M | Conglomerate |
| 19 | UTX | United Technologies | Conglomerate |
| 20 | BA | Boeing | Aerospace and defense |
| 21 | CAT | Caterpillar | Construction and mining |
| 22 | NKE | Nike | Apparel |
| 23 | DWDP | Dow Du Pont | Chemical industry |
| 24 | PG | Procter & Gamble | Consumer goods |
| 25 | TRV | Travelers | Insurance |
| 26 | UNH or H | UnitedHealth Group | Managed health care |
| 27 | VZ | Verizon | Communication |
| 28 | DIS | Walt Disney | Broadcasting |

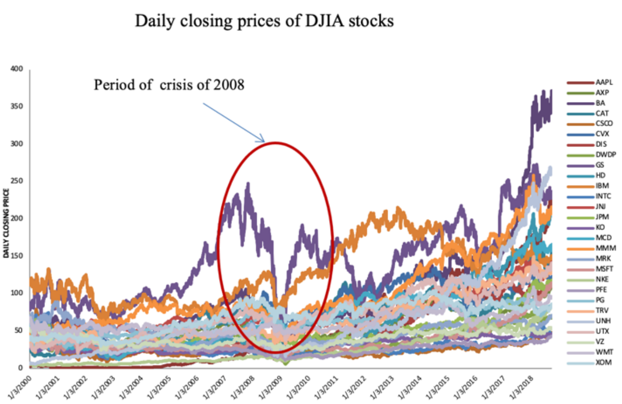


**Fig.1.** Daily closing prices of the DJIA stocks 2000 to 2018

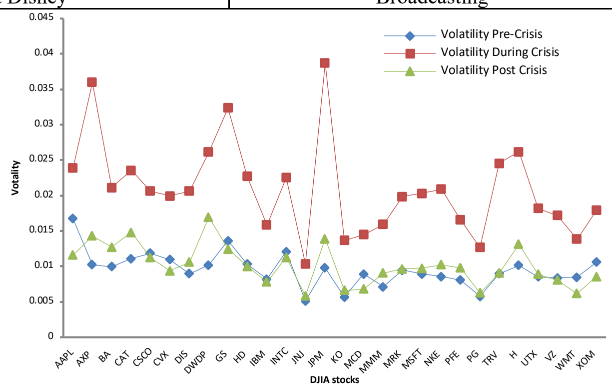


**Fig. 2.** Volatility of the 28 Dow Jones stocks pre, during & post crisis periods.

## 3. Methodology

The techniques of RMT, Network analysis and hierarchical techniques are applied in three considered periods to extract the hidden information from DJIA stocks**.**

### 3.1 Random Matrix Theory

In RMT approach, the eigenvalues (EVS) of Wishart matrix(WM) which is constructed from completely random time series equivalent to considered time series is compared with the correlation matrix of DJIA stocks. The correlation matrix of DJIA stock prices is constructed as follows: The logarithmic returns $L_j(\tau)$ of stock '$P_j(\tau)$' is computed as $L_j(\tau) \equiv \ln P_j(\tau) - \ln P_j(\tau-1)$, where $P_j(\tau)$ is the daily closing prices of the stock '$j$' at time $\tau$.

The normalized returns of the stock '$j$' is defined as $l_j(t) = \frac{L_j(\tau) - \langle L_j \rangle}{\sqrt{\langle L_j^2 \rangle - \langle L_j \rangle^2}}$, where $\langle ... \rangle$ denotes the average time over the considered period. The cross correlation matrix (CCM) is constructed using the normalized returns. The CCM elements $C_{jk} \equiv < l_j(\tau) l_k(\tau) >$ varies from -1 to 1. In RMT, the probability distribution ($P_{rm}(\lambda)$) of eigenvalues (λ) of Wishart matrix is given by,

$$P_{rm}(\lambda) = \begin{cases} \frac{Q}{2\pi} \frac{(\sqrt{(\lambda_{max}-\lambda)(\lambda-\lambda_{min})})}{\lambda} & \lambda_{max} \leq \lambda \leq \lambda_{min} \\ 0 & outside\ above\ range \end{cases}$$

The smallest and largest EVS of WM is given by $\lambda_{max,min} = \left[1 \mp \left(\frac{1}{\sqrt{Q}}\right)\right]^2$. For a random time series, all the eigenvalues of cross correlation matrix (CCM) fall in the limits $[\lambda_{max}, \lambda_{min}]$. Any deviation from this bound indicate correlation in time series. Fig.4 shows the eigenvalue distribution and color map representation of cross-correlation matrices pre, during and post the crisis respectively. The eigenvalue distribution of CCM of empirical data is compared with that of WM and results are summarized in Table-2.

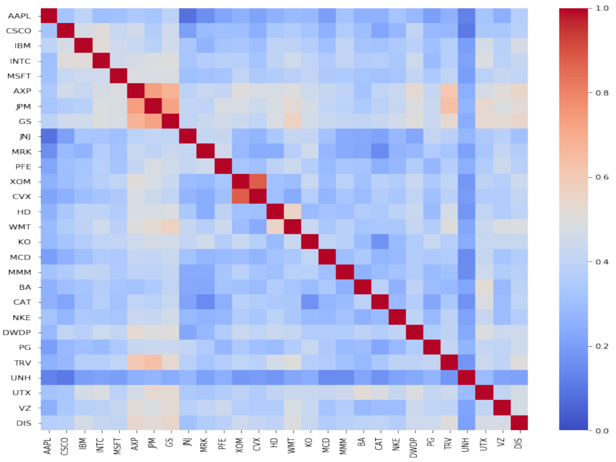

**Fig. 3.** Color map representation of cross correlation matrix in PRC period.

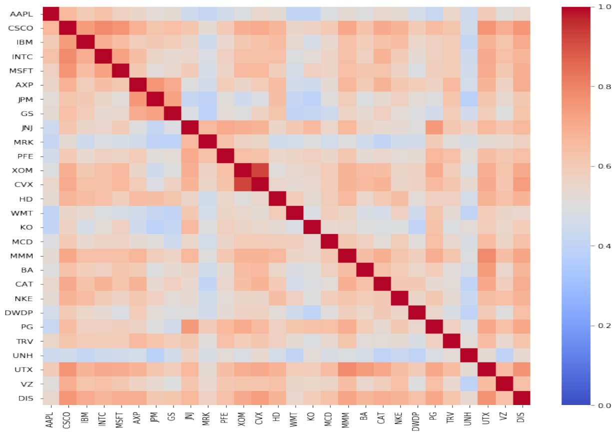

**Fig. 4.** Color map representation of cross correlation matrix in DUC period.

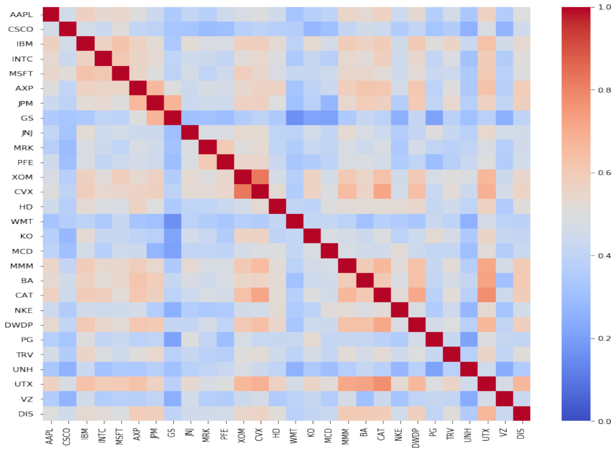

**Fig. 5.** Color map representation of cross correlation matrix in POC period.

The comparison of color maps in the Fig.3 to Fig.5 show that correlation structure changes during the period of crisis. Highly correlated sector of IT stocks is formed during the period of crisis. The EVD of empirical CCM in PRC, DUC and POC periods are shown in Fig.6, Fig.7 and Fig.8 respectively. The LEV of CCM in pre-crisis period is 10.00 which enhanced by 35.7% and become 15.55 during the period of crisis. The LEV in post crisis period is found out to be 12.44.

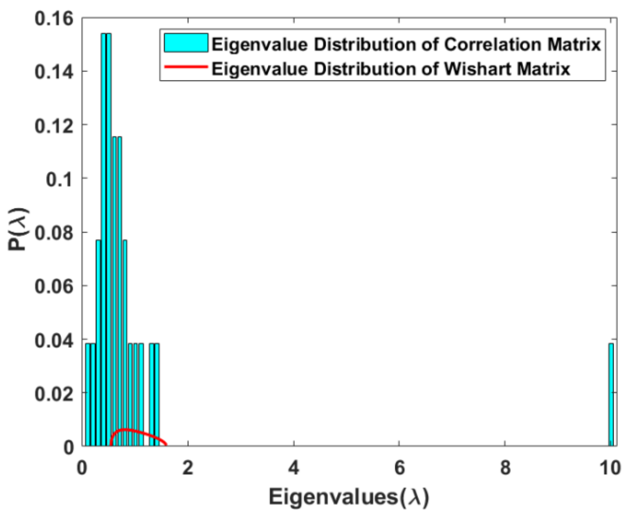


**Fig. 6.** (PRC period) Comparison of EVD of the empirical correlation matrix of DJIA stocks (cyan color) and Wishart matrix (red color).

The LEV which captures the collective dynamics among all stocks increases in DUC period. The eigenvalues outside the RMT predictions in PRC, DUC and POC periods are 50%, 76.90% and 61.50% respectively. LEV increases significantly during crisis/occurrence of extreme events which act as one of the indicator of systematic risk.

From the random matrix theory results (summarized in Table-2), we conclude that the most of the eigenvalues of empirical correlation matrices are outside WM predictions. This shows that the interactions among DJIA stocks are not random but they are revealing.

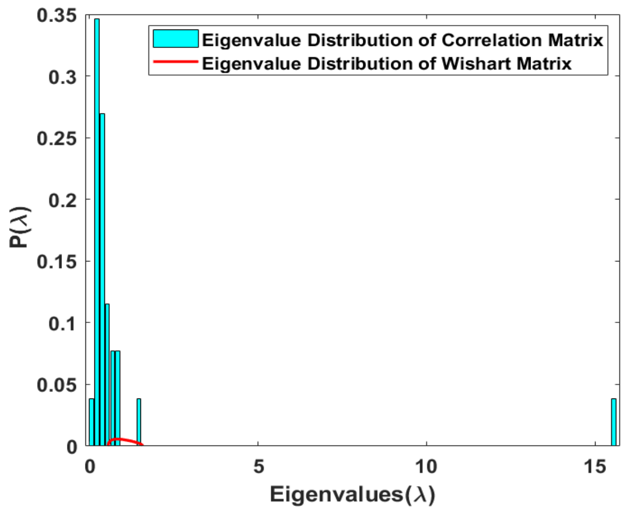


**Fig. 7.** (DUC) Comparison of EVD of the empirical correlation matrix of DJIA stocks (cyan color) and Wishart matrix (red color).

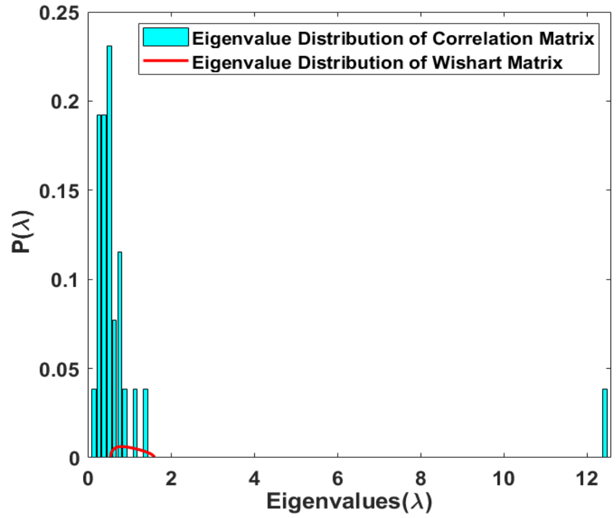


**Fig. 8.** POC period) Comparison of EVD of the empirical correlation matrix of DJIA stocks (cyan color) and Wishart matrix (red color).

**Table 2.** RMT results for DJIA stocks

| Eigenvalues | Wishart matrix | Empirical correlation matrix | | |
|---|---|---|---|---|
| | | PRC Period | DUC Period | POC Period |
| Largest eigenvalue | 1.577316 | 10.00621 | 15.5517 | 12.43613 |
| Smallest eigenvalue | 0.553666 | 0.112017 | 0.06052 | 0.141206 |

### 3.2 Construction of threshold networks

To get information regarding the topology of the DJIA stocks network, we have constructed threshold networks from correlation matrices. The 28 DJIA stocks forms the vertices of the network while correlation among them represent the links among them. A threshold ($\theta$) is considered which decides the links between the nodes. At $\theta = 0$ all the nodes are connected and with increase in the threshold value, the nodes having correlation coefficient less than $\theta$ get disconnected[21]. Therefore different threshold values give rise to networks having same nodes but different connections. The undirected edges ($U$) in the network of DJIA stocks are defined as

$$U = \begin{cases} u_{jk} = 1 \ \ if\ j \neq k \quad \ and\ C_{jk} > \theta \\ u_{jk} = 0 \ \ if\ j = k \end{cases}$$

The correlation networks at different thresholds in PRC, DUC and POC period is constructed using Fruchterman-Reingold (FR) layout [39]. The correlation networks at thresholds ranging from 0 to 0.8 in PRC, DUC and POC period are shown in Fig.9, Fig.10 & Fig.11. The correlation (anti-correlation) between the stocks is shown with green (red) colour. More is the thickness of the green line; more is the correlation between stocks.

### 3.4 Minimum Spanning Tree and Hierarchical Clustering

The analysis of clustering or community structure is most important aspect of a complex network. The metric distances $d_{jk} = \sqrt{2(1 - C_{jk})}$ are used to construct MST of DJIA stocks. A symmetric distance matrix ($D$) is computed using metric distances $d_{jk}$ having elements in the range from 0 to 2 [25,40]. We have used the Prim's algorithm [41] for drawing the MST of stocks. Hierarchical clustering produced by agglomerative method or divisive method is shown by a 2-dimensional graph called dendrogram.

We have used the average linkage clustering to produce best tree like dendrograms[42,43] which describe the hierarchy in the stocks of DJIA .The minimum spanning trees and dendrograms of the DJIA stocks in PRC, DUC and POC periods are shown in Fig.12 and Fig.13 respectively.

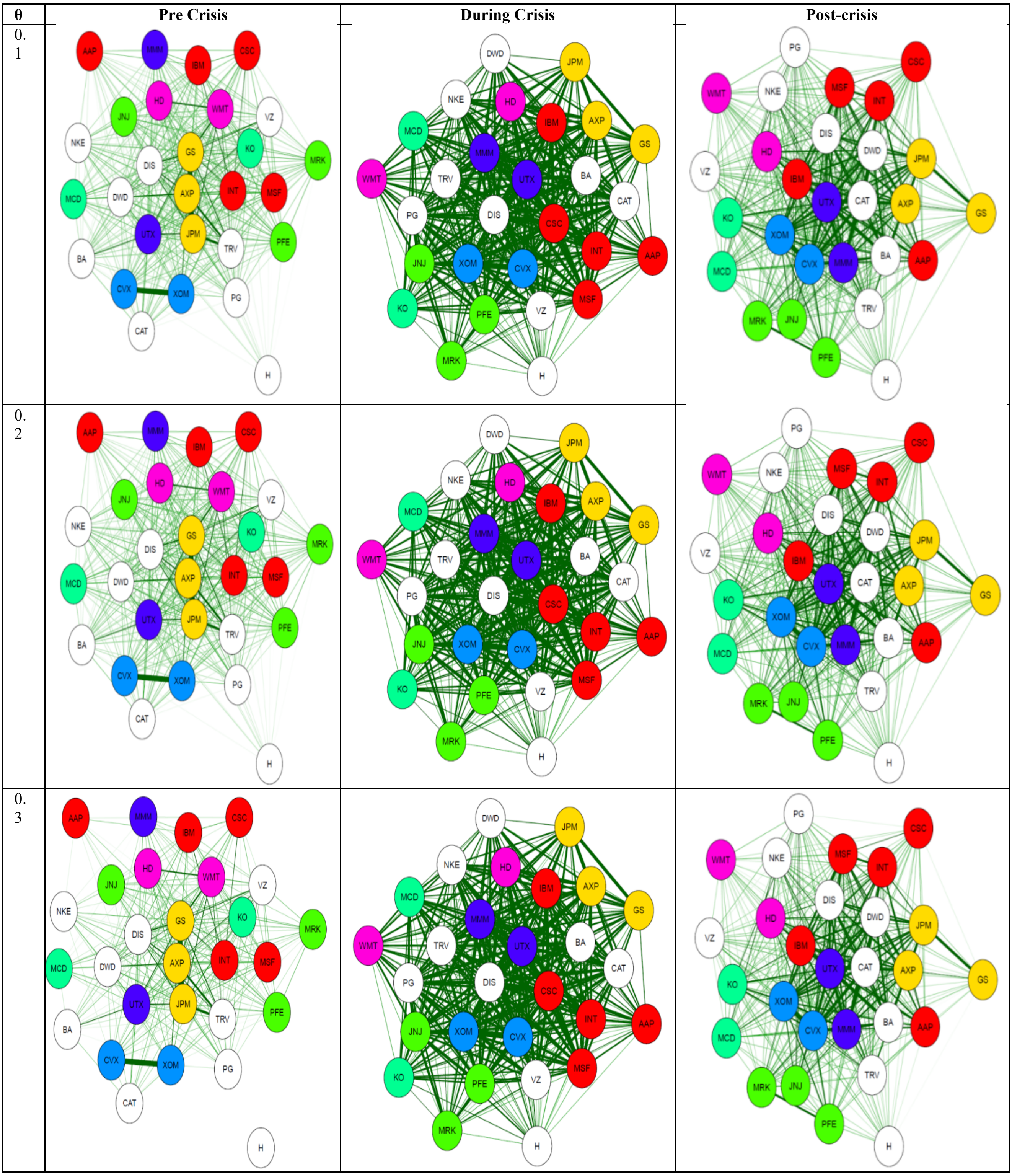


**Fig. 9.** Networks of DJIA Stocks in pre-crisis, during crisis and post-crisis periods at thresholds (θ) = 0.1 to 0.3. Different sectors; IT, Finance, Pharmaceutical, food, oil-gas, conglomerate and retail sectors are shown with red, yellow, green, light green, blue, light blue, and purple respectively.

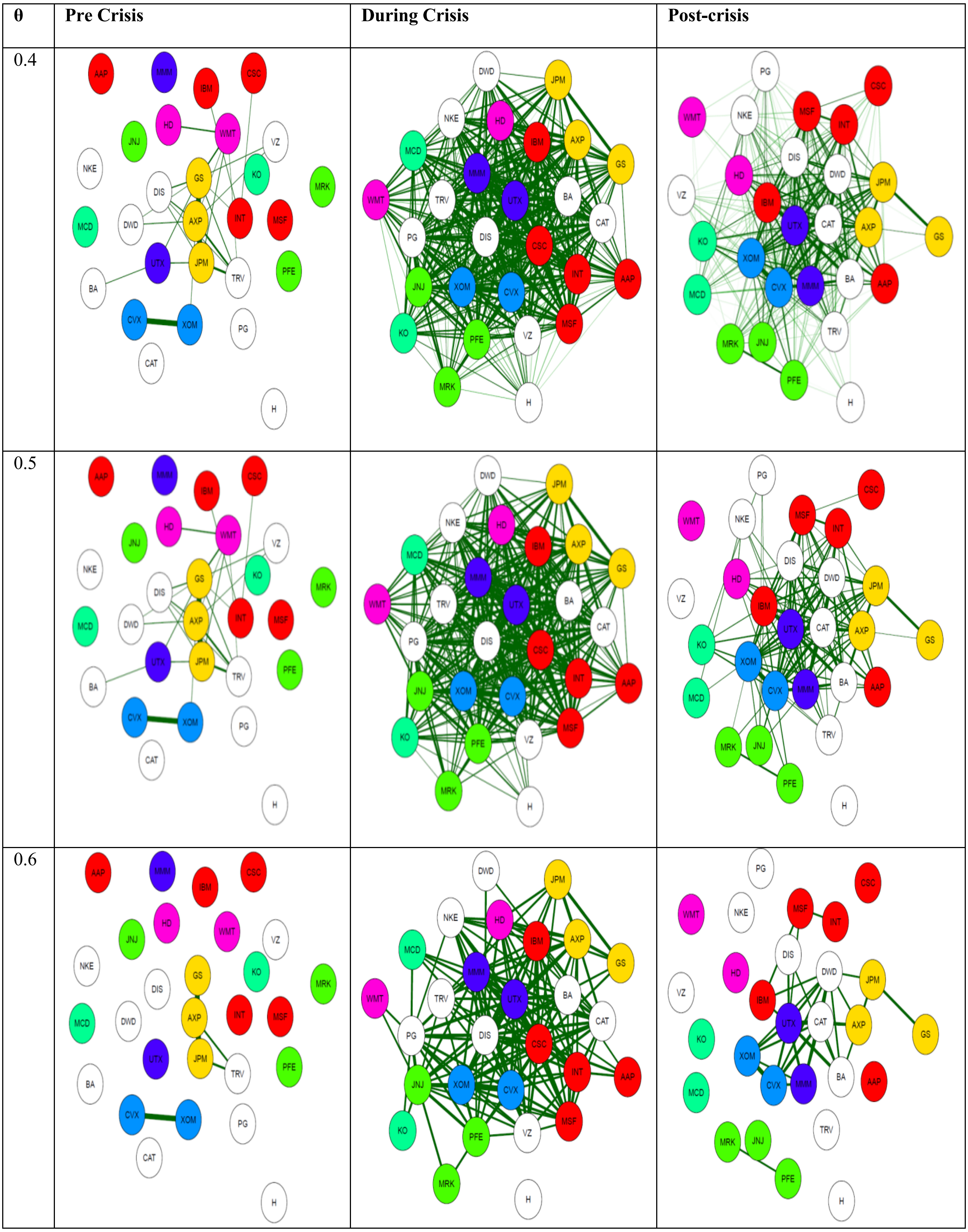


**Fig.10.** Networks of DJIA Stocks in pre-crisis, during crisis and post-crisis periods at thresholds (θ) = 0.5 to 0.6. Different sectors; IT, Finance, Pharmaceutical, food, oil-gas, conglomerate and retail sectors are shown with red, yellow, green, light green, blue, light blue, and purple respectively.

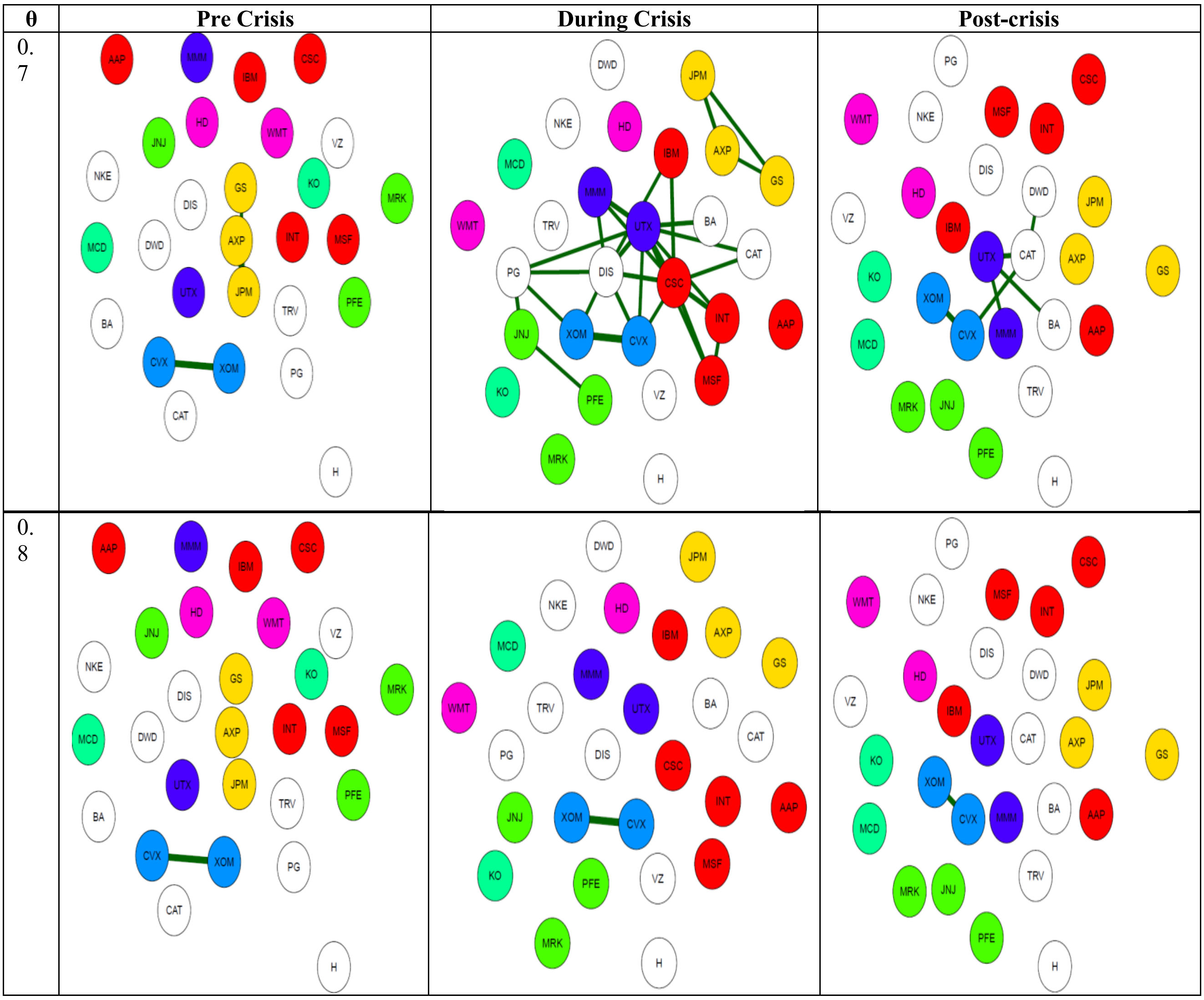


**Fig.11.** Networks of DJIA Stocks in pre-crisis, during crisis and post-crisis periods at thresholds (θ) = 0.7 to 0.8. Different sectors; IT, Finance, Pharmaceutical, food, oil-gas, conglomerate and retail sectors are shown with red, yellow, green, light green, blue, light blue, and purple respectively.

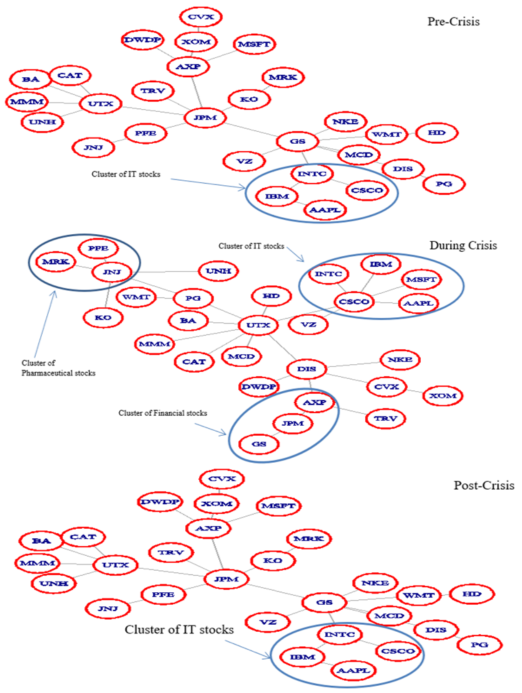


**Fig. 12.** Minimum Spanning Tree of Dow Jones stocks in PRC, DUC and POC periods respectively

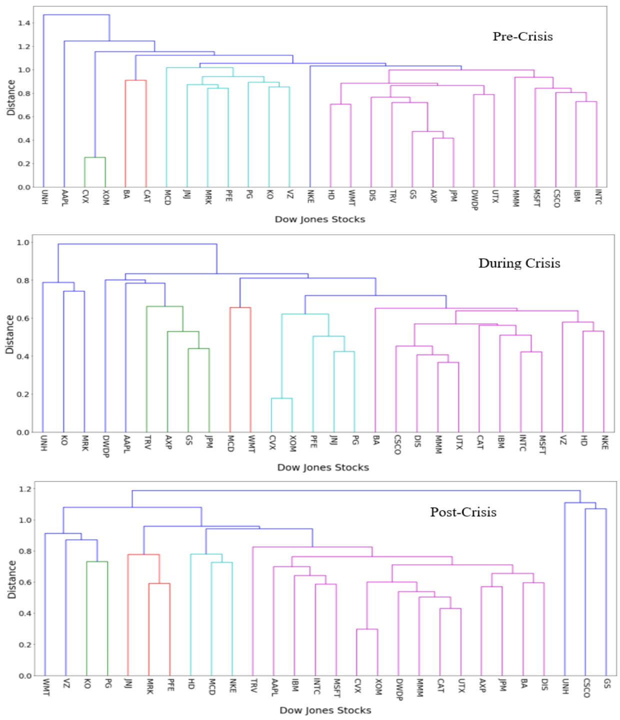


**Fig. 13.** Dendrogram of Dow Jones stocks in PRC, DUC and POC periods respectively.

The average shortest path length (ASPL) of a network is computed using the relation; $ASPL = \frac{\sum\sum_{j>i} d(V_i,V_j)}{\binom{N}{2}}$, where $d_i$is the degree of the node $V_i$ and N is number of nodes [44]. The ASPL of network of DJIA stocks at θ =0 is 2.9503, 1.7718 and 2.2778 in PRC, DUC and POC periods respectively

## 4. Centrality Measures

The centrality measures provide information related to most significant, central and most between stocks. We have calculated degree centralities, closeness centralities, between centralities and clustering coefficient of the correlation based networks of DJIA stocks in different period of crisis. The degree centrality captures the node having high prominence or popularity in the network. The most central node plays significant role in controlling and spreading the flow of information/rumour [49]. Degree Centrality is equal to the degree of node $V_i$ and do not ruminate topology of entire network. The Closeness Centrality and Betweenness Centrality are examples of flow based centralities [49]. Closeness centrality is extension of degree centrality by considering all size neighbours. Betweenness centrality considers the number of shortest paths passing through the node**.** The degree centrality, closenesss centrality, clustering coefficient and betweenness centrality of the DJIA stocks at zero threshold in PRC,DUC and POC periods as shown in the Fig.14, Fig.15, Fig.16 and Fig.17 respectively.

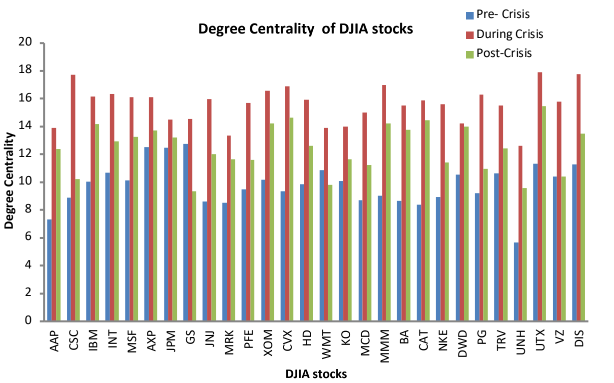


**Fig. 14.** Degree centrality of DJIA stocks in PRC, DUC and POC periods.

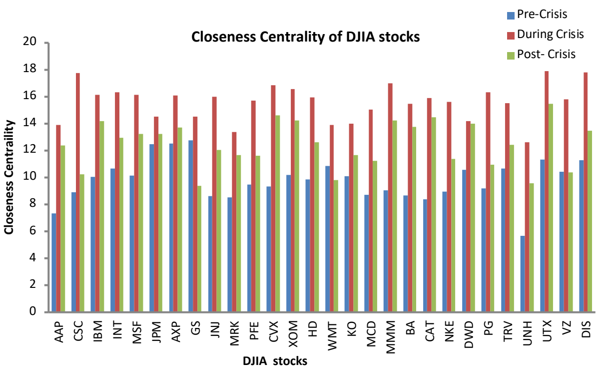


**Fig. 15.** Closenesss centrality of DJIA stocks in in PRC, DUC and POC periods.

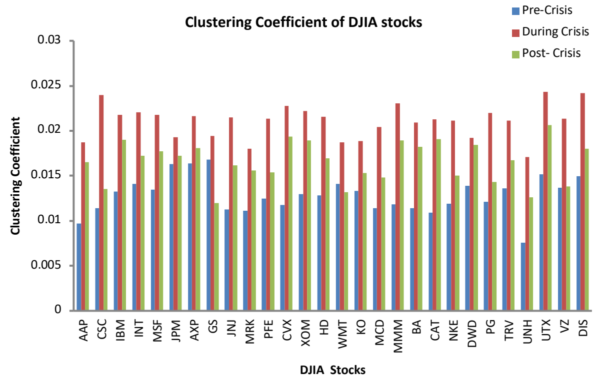


**Fig. 16.** Clustering coefficient of DJIA stocks in in PRC, DUC and POC periods.

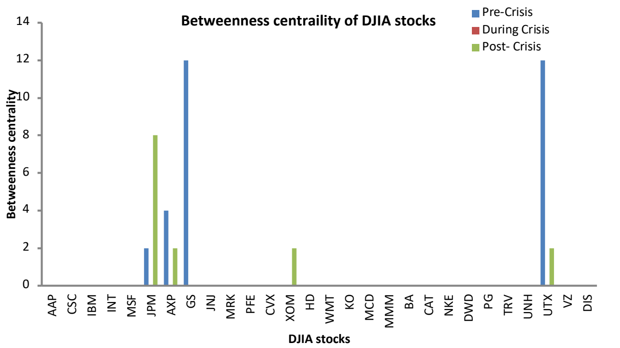


**Fig. 17.** Betweenness centrality of DJIA stocks in PRC, DUC and POC periods.

To check the validity of present analysis in the covid-19 period, data is taken up to 2021. The considered time period of 21 year is classified into 143 overlapping time spans, each of one year duration. Average volatility of DJIA stocks is plotted in Fig.18. The distinct peaks are identified revealing the happening of extreme events. Happening of extreme events is indicated by high volatility. The graph identifies extreme events such as; Dot-com Bubble, GFC8, European sovereign debt crisis, Chinese Crisis and Covid-19.

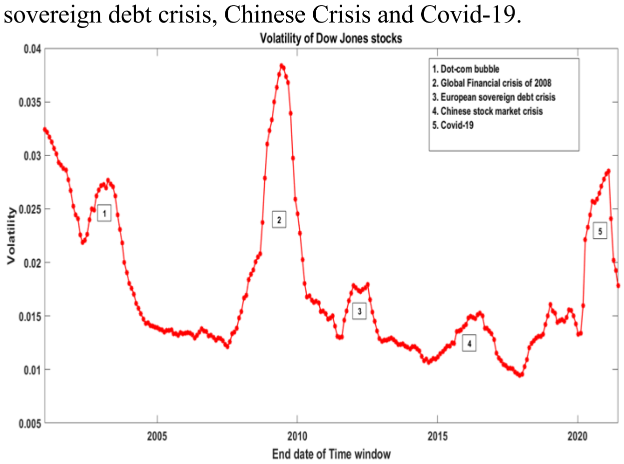


**Fig.18.** Mean volatility in rolling overlapped time windows of one year.

The mean correlation is computed in each overlapped rolling window and plotted in the Fig.19. The peaks are detected during the extreme events. The mean correlation coefficient of DJIA stocks found to be enhanced during extreme events; Dot-com Bubble, GFC8, European sovereign debt crisis, Chinese Crisis and Covid-19.

## 5. Results and Discussion

The RMT analysis indicates that the data used in this analysis is not completely random but informative. The eigenvector associated with LEV of CCM indicates the presence of correlation in the time series. The LEV of the CCM has increased significantly during the period of crisis. This shows that the FC08 has significant effect on structure and dynamics of DJIA stocks network. The color map (Fig.5) in the DUC period depicts high correlation among DJIA stocks. In the correlation networks at different thresholds (Fig.9, Fig.10 and Fig.11), DJIA stocks are fully connected up to threshold of 0.2, 0.5 and 0.4 in PRC, DUC and POC periods. The correlation among stocks has increased significantly during the crisis period as compared to that in PRC and POC periods. The complex network analysis supports the RMT results. The Chevron (CVX) and Exxon Mobil (XOM) which are Oil and Gas companies are found to be highly correlated stocks in all periods of analysis. United health Group (UNH or H) which is a managed healthcare company is found to be weakly correlated in all periods. The results of the threshold networks are summarized in the Table-3.

**Table 3.** Strongly and weakly correlated (connected) stocks in PRC, DUC and POC periods

| **Period** | **Strongly Correlated (connected) stocks (Decreasing order)** | **Weakly Correlated (connected) stocks (Decreasing order)** |
|---|---|---|
| Pre Crisis | CVX,XOM,GS,AXP &JPM | UNH,AAP,MMM,JNJ,CAT,MRK |
| During Crisis | CVX,XOM | UNH,AAP,MRK,WMT,MCD,DWD,NKE |
| Post Crisis | CVX,XOM | AAP,WMT,VZ, MCD, KO, HD, NKE |

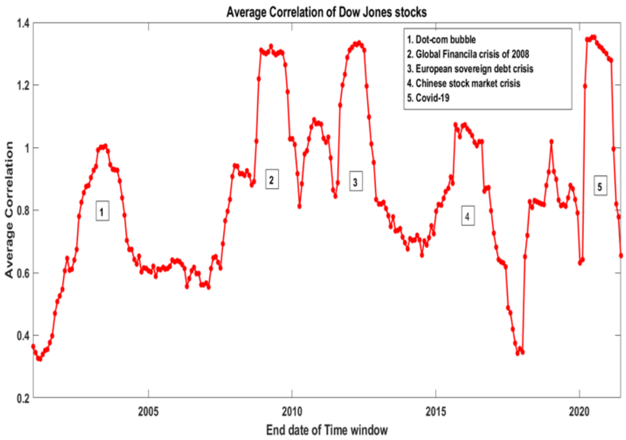


**Fig. 19.** Average value of correlation coefficient in rolling overlapped time windows.

The clustering coefficients of all DJIA stocks are observed to be higher during the crisis period representing high clustering among stocks. During the period of crisis, ASPL of network decreases. This indicates higher closeness among DJIA stocks. Degree and closeness centralities of DJIA networks increases in DUC period. These results show high correlations and closeness among stocks in this period. In conclusion, the investigation shows that during the period of crisis, there are significant changes in the structure and dynamics of the network of DJIA stocks. The betweenness centralities of all DJIA stocks are zero during the crisis period which indicates that stocks prefer to get clustered instead of coming in between the network.

The MST in pre-crisis period (shown in Fig.12) has one cluster of IT stocks. The United Technologies (UTX), JPMorgan Chase (JPM) and Golden Sachs (GS) are found to be hub vertices in pre-crisis period. Three clusters (IT stocks, Pharmaceutical stocks and financial stocks) are formed during the period of crisis. United Technologies (UTX), Johnson & Johnson (JNJ), Cisco systems (CSCO) and Walt Disney (DIS) are hub vertices during the period of crisis. The MST in POC period shows one cluster of IT stock. The United Technologies (UTX) emerged as the major hub vertex in this period. The MST analysis shows high tendency of clustering during the crisis period.

In the analysis of dendrograms (Fig.13), different sectors are identified that are shown by different colors. These sectors in DJIA stocks are found to change their group in the different periods of crisis. By cutting the dendrograms at stem length of 1.1, give rise to different clusters in PRC, DUC and POC periods. Two dominant clusters; one comprising of IT companies, financial companies and retail companies (shown with violet color) and second comprising of pharmaceutical and food companies (shown with sky blue color) are formed in the pre-crisis period. Only one big cluster consisting of all DJIA stocks is formed during the period of crisis showing the increased hierarchy among stocks.

## 6. Conclusions

The analysis of time series of DJIA stocks using techniques of RMT, threshold network and hierarchical clustering is carried out. Following conclusions can be drawn from the analysis

- The RMT analysis of the 28 DJIA stocks revealed that interaction among DJIA stocks can provide significant information.
- The largest eigenvalue of CCM lies beyond WM bounds representing market mode.
- Network analysis depicts high correlation among the DJIA stocks during the crisis period.
- MST analysis show clustering is significantly high during the crisis.
- Degree, closeness centralities and clustering coefficients of all DJIA stocks increases during the crisis period which shows high correlation and closeness among stocks.
- The analysis in moving time window is found to detect Dot-com Bubble, GFC8, European sovereign debt crisis, Chinese Crisis and Covid-19.
- The findings of present study are helpful in understanding of similar crisis in future and in determining the corrective measures for the same.

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