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An Econophysics Approach to Analyse the Correlations in the Stocks of S&P 500 Index of India

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ABSTRACT: The occurrence of extreme events changes correlations in financial markets significantly. The identification of trend of stock price variation which results into financial bubble has been a challenging task. In the present investigation an attempt is made to understand the structure and dynamics of the Indian stock market in the wake of the global financial crisis of 2008 erupted in the US. We have studied the time series of 128 stocks of S&P 500 index of India. We have considered three durations in the time series as pre, during and post crisis. We have constructed correlation matrices based on Pearson correlation among the stocks in three considered periods. We have applied the random matrix theory to test the economic importance of the data. We have applied the complex network approach and constructed correlation based networks. We have distinguished various extreme or critical events and proposed indicator of the systemic risk. The findings of present study are beneficial in understanding of similar crises in future and in deciding the remedial actions for the same. These investigations also found applications in portfolio designing and risk management.

Keywords: Correlation matrices, Complex networks, Inverse participation ratio, Random matrix theory, Threshold Networks, Volatility,

Abbreviations: CS, complex systems; FM, Financial Markets; GFC08, Global Financial Crisis of 2008; RMT, Random Matrix Theory; CAN, Complex Network Analysis; CCM, Cross-Correlation Matrix; EVS, Eigenvalues; EVD, Eigenvalue Distribution; EVR, Eigenvector; CBN, Correlation Based Networks; $DJIA_{US}$, Dow Jones Industrial Average; NYSE, New York Stock exchange; PMFG, Planar Maximally Filtered Graphs; ISM, Indian stock Market; NSE, National Stock Exchange; WWW, World Wide Web; BSE, Bombay Stock Exchange; LEV, Largest Eigenvalue.

I. INTRODUCTION

In our daily life we came across many complex systems associated with nature, society and infrastructure. In nature climate, organism, human brain and ecosystem are examples of complex systems. In society economy, collaboration, friendships are the complex systems. The internet, power grids, World Wide Web (www), transport, telecommunication are example of complex systems (CS) in infrastructure sector [1]. Human ability to reason and comprehend makes human brain a very complex system which requires the coherent activity of billions of neurons. Our society is very good example of complex system which is formed from millions of individuals. The society requires cooperation among all individuals forming the society. Human brain is at base and natural language is one of its emergent constructions. No development in the civilization is possible without language. The Financial Markets (FM) is the creation of human civilization. The FM are the creation of human civilization. The financial markets are one of the most important complex systems. Financial markets form open systems, where inflow and outflow of the investments represent the energy of the system. The investor's decisions are often influenced by a solid irrational component. The irrational component in investors decisions result in herding behaviour which led to bubbles and crashes [4]. Due to incomplete knowledge of market, investors are not able to decide the genuineness of embedded information in asset price. The overestimation of the embedded information result in positive feedback which degrades the association among asset value and the information content [5]. Bubbles and crises break the equilibrium state of the market. Bubbles and crises are connected to the volatility assembling. Volatility is presence of consecutive eras of major magnitude of price variations. Volatility clustering indicates prolonged existence of fluctuation amplitude. The estimation of number of internal or external factors affecting the structure and dynamics of market is difficult. The intelligence of investors results in unevenly fast self-organization of financial markets and enhancement in their complexity [6-8]. So the construction of realistic market models is a very challenging task. The financial markets have been studied by researchers from economics, mathematics and physics background [9]. The correlations among the time series of the stocks have been widely investigated by the physicists [9, 10]. The nature of financial time series and the correlation among them are very The study of financial markets is very important for developing and designing investment strategies [11]. The interacting components of the financial markets form complex networks at different stages result in self-organisation of financial markets. The frequency of occurrence of financial crisis is more than the expectation of the investors. Due to the financial crises, the stock markets experience rapid changes like phase transitions. The structure of the correlation among the stocks modifies during the crisis. So the understanding of time evolution of stock market is very beneficial and important. The study of correlation among stock markets, time evolution of the correlation has become popular research field in the past years [12].

Stock markets are accompanied by uncertainties. To understand the trend of variations of cost of stocks resulting into up and downs in FM is a difficult task. Global financial crisis of 2008(GFC08) is a severe economic crash. The GFC08 erupted in the United States of America and then spread to the whole of the world. The GFC08 is started in 2007 and despite the efforts of US Federal reserve for its prevention; it affects most of the stock markets around the globe. It is a very difficult task to give any prediction about such crisis. Many empirical models based on the physics and statistical theories [1-12] have been applied to study the complexity of the financial markets. Various techniques or methods based on the concept of physics and mathematics have been used by the researchers to extract information from financial databases. Many approaches based on physical phenomenon have been used to analyse the financial market [13-23]. The Brownian motion, entropy, random walk, chaotic motion and turbulence are few phenomena which have been used in the past to study the financial markets. The statistical and quantum mechanics have been used in many studies to describe the complex nature of stock markets [24, 25]. Random matrix theory (RMT) and complex network analysis (CNA) have been used extensively in the analysis of time series of global financial markets.

RMT is one of the extensively used techniques for investigation of correlations in stocks [2, 10, 25-34]. RMT was originally established in 1967 by Wigner [26] by explaining nuclear spectra in terms of statistical properties of eigenvalues (EVS) of large random matrices. Since then RMT has been used as an effective and useful tool for analysis in numerous areas; Physics, nano-devices, ultrasonic, underwater acoustics, geophysics, seismology and financial markets [9, 34]. RMT analysis involves the comparison of eigenvalue distribution (EVD) of correlation matrix constructed from random time series with the EVD of the cross-correlation matrix (CCM) constructed from empirical time series. In RMT approach, the deviations of eigenvalues of CCM from the RMT predictions (largest and smallest eigenvalues of Wishart matrix) show the existence of information in dataset.

The RMT have been used successfully in FM for the portfolio management [35–40]. RMT have been used to identify genuine correlations among stocks [41]. Kumar and Deo [34] have used RMT to investigate correlation important in the field of Econophysics.

among the dominant indexes of global stock markets Zheng *et al.* [42] have observed direct connection between variations in correlation and occurrence of booms or bubbles. In CNA the financial markets are represented by networks where stocks form the nodes of the network and some statistical measures of interactions among stocks are the links connecting the nodes.

The complex network approach has been used to investigate financial markets of various countries [43-50]. The weighted networks connecting various elements of the system have been used to study FM. The credit of construction of correlation based networks (CBN) goes to Mantegna [51]. He investigated the DJIA and S&P 500 of US using CBN. Onnela *et al.* [52] have investigated NYSE using CBN. Tumminello *et al* [53] have used PMFG to investigate topology of NYS. In our previous study [54] we have studied the stability of BSE SENSEX and NIFTY50 index. From the literature survey, we can conclude that different techniques have been applied to different stock markets all around the globe but very less systematic work studying the structure and dynamics of Indian stock market is available. We didn't find any work in which Indian stock market is analysed using different techniques and outcomes are compared with results available for global markets. We find very little systematic work where impact of different extreme or critical events on the Indian stock market has been investigated.

In the present work we study the structure and dynamics of network of S&P 500 stocks. The S&P 500 is leading stock market index of ISM. This index covers around 96% of market capitalization. Around 93% of the total turnover on NSE of India is represented by S&P 500.The organization of paper is as follows: in section-II, we discuss the filtration of data and techniques used. In section-III, we discuss the results and conclude the findings of the investigation in section-IV.

II. DATA DESCRIPTION AND METHODOLOGY

We have analyzed the database of 128 dominant stocks of S&P 500 index of India. The daily closing price of 128 companies of S&P 500 India (detailed description is given in Table 1) from 2006 to 2018 is taken from Lal Bahadur Shastri Institute of Management, New Delhi. We have filtered the data using the technique opted by Lynall *et al.* [55]. The mean variance (volatility) of returns of the stocks is calculated for sliding time window of one year with a shift of one month. The volatility of the S&P 500 stocks is plotted in the Fig.1.The GFC08 erupted in the USA and then spread to the all the countries around the globe. To study the impact of GFC08 on the Indian stock market, we consider 3 sub-periods. The periods from 7/6/2006 to 30/11/2007 and 1/12/2007 to 306/2009 are considered as "pre-crisis" and "during the crisis" respectively. The period from 1/1//2010 to 30/6/2011 is considered as "post-crisis". We have applied the techniques of RMT and CNA to reveal the hidden information from time series of 128 S&P 500 stocks.

Table 1: List of the S&P 500 stocks studied in investigation.

Abbre.	Full Name	Sector	Abbre.	Full Name	Sector
TTMT	TATA Motors Ltd		GLXO	GlaxoSmithKline PhamaceuticalsLtd	HEA
MM	Mahindra and Mahindra Ltd	CD	APHS	Apollo Hospitals	HEA
HMCL	Hero MotoCorpLtd	CD	PIEL	Piramal Enterprises Limites	HEA
BOS	Bosch Ltd	CD	TRP	Torrent Pharmaceuticals Ltd	HEA
MSS	MothersonSumi Systems Ltd	CD	IPCA	IPCA Labs Ltd	HEA
TTAN	Titan Company Ltd	CD	SANL	Sanofi India Limted	HEA
Z	Zee Entertainment Private Ltd	CD	PFIZ	Pfizer Ltd	HEA
BHFC	Bharat Forge Company Ltd	CD	NTCPH	NATCO Pharmaceuticals Ltd	HEA
EXID	Exide Indus Ltd	CD	LT	Larsen and Toubro Ltd	IND
APTY	Apollo Tyres Ltd	CD	BHEL	Bharat Heavy Electricals Ltd	IND
MRF	MRF Ltd	CD	SIEM	Siemens Ltd	IND
IH	Indian Hotels Company Ltd	CD	CCRI	Container Corp. of India	IND
BATA	Bata India Ltd	CD	ABB	ABB India Ltd	IND
BIL	Balkrishna Industries Ltd	CD	EIM	Eicher Motors Ltd	IND
EIH	EIH Ltd	CD	KKC	Cummins India Ltd	IND
WHIRL	Whirlpool of India Ltd	CD	BHE	Bharat Electronics Ltd	IND
TC	Thomas Cook Ltd	CD	HAVL	Havells India Ltd	IND
SF	Sundram Fasteners Ltd	CD	GDSP	Godrej Industries Private Ltd	IND
BBTC	Bombay Burmah Trading Corp. Ltd.	CD	ENGR	Engineers India Ltd	IND
KRB	KRBL Ltd.	CD	AMRJ	Amara Raja Batteries Ltd	IND
ITC	ITC Ltd	CD	VOLT	Voltas Ltd	IND
HUVR	Hindustan Unilever Ltd	CS	SKF	SKF India Ltd	IND
DABUR	Dabur India Ltd	CS	3M	3M India Ltd	IND
CLGT	Colgate Palmolive	CS	FNXC	Finolex Cables Ltd	IND
SKB	GlaxoSmithKline	CS	GRIL	Graphite India Ltd	IND
MRCO	Marico Ltd	CS	ESC	Escorts Ltd	IND
PG	Procter and Gamble Ltd	CS	AL	ashokaleyland ltd	IND
BRIT	Britannia Industries Ltd	CS	HEG	HEG ltd	IND
TGBL	TATA Global Beverages Ltd	CS	SCHFL	Schaeffler India Ltd.	IND
GILL	Gillette India Ltd	CS	INFO	Infosys Ltd	IT
AISG	Asahi India Glass Ltd	CS	WPRO	WIPRO Ltd	IT
ONGC	Oil and Natural Gas Corp. of India	CS	MPHL	MphasisLtd	IT
RIL	Reliance Industries Ltd	EN	HEXW	Hexaware Technologies Ltd	IT
IOCL	Indian Oil Corp.Ltd	EN	HWA	Honeywell Automation India Ltd	IT
BPCL	Bharat Petroleum Corp.Ltd	EN	CYL	CyientLtd	IT
HPCL	Hindustan Petroleum Corp.Ltd	EN	TELX	TATA ElexsiLtd	IT
MRPL	Mangalore Refinery and Petrochemicals Ltd	EN	HZ	Hindustan Zinc Ltd	MAT
HDFCB	Great Eastern Shipping Company Ltd	EN	APNT	Asian Paints Ltd	MAT
SBIN	Gujarat Mineral Development Corp.Ltd	FIN	TATA	TATA Steel Ltd	MAT
ICICIBC	ABAN Offshore Ltd	FIN	SAIL	Steel Authority of India Ltd	MAT
HDFC	HDFC Bank Ltd	FIN	HNDL	Hindalco Industries Ltd	MAT
AXSB	Axis Bank Ltd	FIN	ACEM	Ambuja Cements Ltd	MAT
KMB	Kotak Mahindra Bank Ltd	FIN	GRASIM	Grasim Industries Ltd	MAT
BOB	Bank of Baroda	FIN	JSTL	Jindal Steel and Power Ltd	MAT
IIB	IndusInd Bank Ltd	FIN	ACC	ACC Ltd	MAT
SHTF	Shriram Transport Finance Ltd	FIN	SRCM	Shree Cement Ltd	MAT
BOI	Bank of India	FIN	PIDI	Pidilite Industries Ltd	MAT
IDBI	IDBI Bank Ltd	FIN	CSTRL	Castrol India Ltd	MAT
LICHF	LIC Housing Finance Ltd	FIN	NACL	National Aluminium Company Ltd	MAT
RCAPT	Reliance Capital Ltd	FIN	UPLL	UPL Ltd	MAT
BJHI	Bajaj Holdings and Investment Ltd	FIN	BRGR	Berger Paints Ltd	MAT
CRISIL	CrisilLtd	FIN	TTCH	TATA Chemicals Ltd	MAT
BAF	Bajaj Finance Ltd	FIN	KNPL	KansalNerolac Paints Limted	MAT
FB	Federal Bank Ltd	FIN	TRCL	Ramco Cements Ltd	MAT
GRHF	Gruh Finance Ltd	FIN	SI	Supreme Industries Ltd	MAT
CIFC	Cholamandalam Investment and Finance Company Ltd	FIN	CENT	Century Textiles and Industries Ltd	MAT
DEWH	Dewan Housing Finance Corp.Ltd	FIN	GFLC	Gujarat FluorochemicalsLtd	MAT
CUBK	City Union Bank	FIN	PI	PI Industries Ltd	MAT
JM	JM Financial Ltd	FIN	BASF	BASF India Ltd	MAT
SUNP	Sun Pharmaceutical Industries Ltd	FIN	ATLP	AtulLtd	MAT
LPC	LupinLtd	HEA	VEDL	vedanta ltd	MAT
DRRD	Dr. Reddy's Laboratories Ltd	HEA	GAIL	GAIL India Ltd	UTI
CIPLA	CIPLA Ltd	HEA	TPWR	TATA Power Company Ltd	UTI
ARBP	Aurobindo Pharmaceuticals Ltd	HEA	RELI	Reliance Infrastructure Ltd	UTI

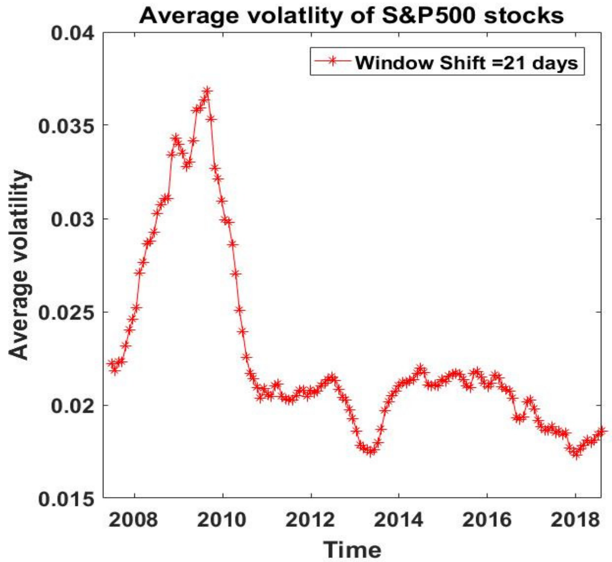

Fig.1. Average volatility of 128 S&P 500 stocks.

A. Random Matrix Theory

In RMT approach, we calculate the eigenvalues of Wishart matrix which is constructed from completely random time series of the same length(L) as that of empirical time series.

The CCM of S&P 500 stock prices is constructed as follows: Let $PR_j(\tau)$ denote the daily closing prices of the stock '*k*' at time *τ* (k= 1, 2, …..m). The logarithmic returns $L_k(\tau)$ of stocks is defined by $L_k(\tau) \equiv \ln PR_k(\tau) - \ln PR_k(\tau-1)$

Then the normalized returns of the stock 'k' is defined as

$$NL_k(t) = \frac{L_k(\tau) - \langle L_k \rangle}{\sqrt{\langle L_k^2 \rangle - \langle L_k \rangle^2}},$$

where$\langle \dots \rangle$ represent the time average over the period of study.

The normalized returns are used in the construction of cross correlation matrix having elements

$$Corr_{km} \equiv < NL_k(\tau) NL_m(\tau) >$$

lying in the range [-1, 1].

The value of $Corr_{km} = 1, -1\ \&\ 0$ corresponds to perfect correlation, perfect anti-correlation and no correlation in stocks respectively. In the limiting values of m and LT (m→ ∞, L → ∞) with ratio$\gamma = \frac{L}{m} \geq 1$, the probability distribution ($P_{rand}(\eta)$) of eigenvalues (η) of Wishart matrix is given by,

$$P_{rand}(\eta) = \begin{cases} \frac{\gamma}{2\pi} \frac{(\sqrt{(\eta_{max} - \eta)(\eta - \eta_{min})})}{\eta} & \eta_{max} \leq \eta \leq \eta_{min} \\ 0 & \text{outside above range} \end{cases}$$

The smallest and largest eigenvalue of the random matrix is given by

$$\eta_{max,min} = \left[1 \mp \left(\frac{1}{\sqrt{\gamma}}\right)\right]^2.$$

For a random data, all the eigenvalues of CCM fall in the limits $[\eta_{max}, \eta_{min}]$. Any deviation from this bound indicate the presence of economic information in time series.

The eigenvalue distribution (EVD) of cross-correlation matrices in pre, during and post-crisis periods are shown in the Fig. 2, Fig. 3 and Fig. 4 respectively.

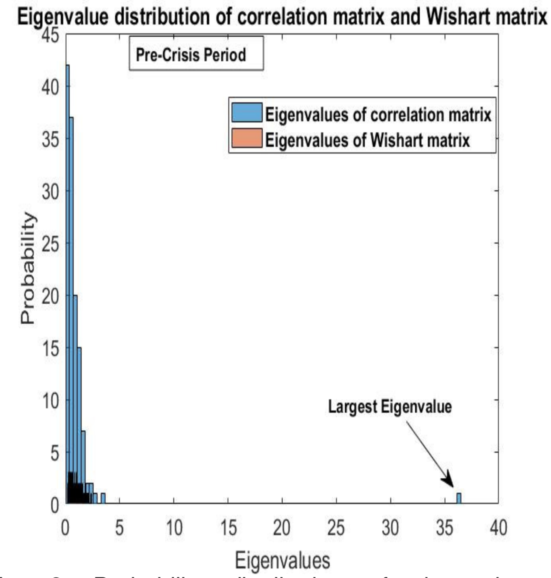

Fig. 2. Probability distribution of eigenvalues of correlation matrix of S&P 500 stocks in pre-crisis period.

The EVD of CCM constructed form the daily returns of S&P 500 stocks are compared with EVD of Wishart matrix and results are summarized in Table 2.

Table 2. Summary of RMT outcomes for S&P 500 stocks.

EVS	Wishart Matrix	Empirical correlation Matrix		
		Pre-Crisis	During Crisis	Post-Crisis
Largest	2.4740	36.482	44.239	29.606
Smallest	0.1824	0.0920	0.0695	0.0981

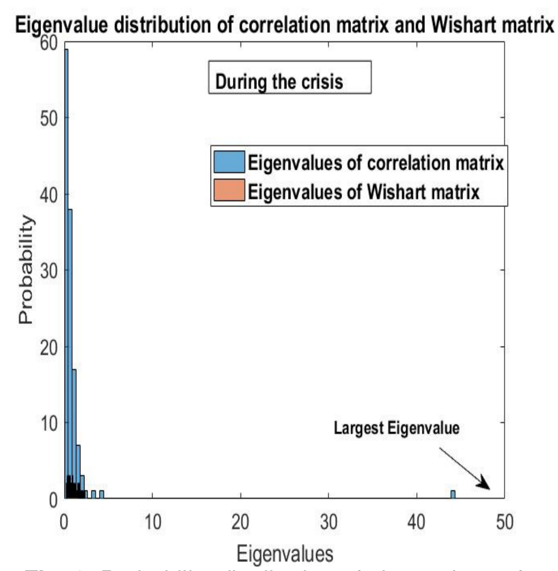

Fig. 3. Probability distribution of eigenvalues of correlation matrix of S&P 500 stocks during crisis period.

We find that the numbers of EVS which are smaller than the smallest eigenvalue of Wishart matrix increases during the period of financial crisis. In random matrix theory, the elements of the 2nd largest EVS provide clustering information. The components of EVR corresponding to Ist and 2nd LEV in period-I, Period-II and Period –III which are the pre, during and post-crisis periods are in shown in the Fig. 6.

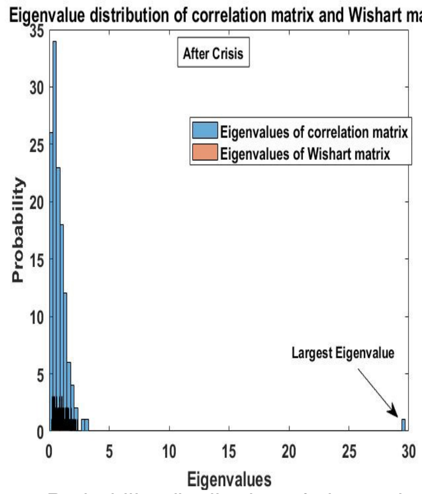

Fig. 4. Probability distribution of eigenvalues of correlation matrix of S&P 500 stocks in post-crisis period.

Most of the EVS of CCM in pre-crisis, during crisis and post-crisis periods fall beyond the RMT predictions. This indicates that the data under consideration is not completely random but contain economically important formation. The findings of the RMT approach are listed in the Table 2. The first largest eigenvalue (LEV) of the CCM represent the market mode and give the collective dynamics of the stocks. The second largest eigenvalue provide the information related to sector or cluster formation among the stocks. The first and second LEV lie out the bounds of Wishart matrix in all the considered periods

The numbers of EVS which are smaller than the smallest eigenvalue of Wishart matrix and number of eigenvalues which are greater the largest eigenvalue of the Wishart matrix are computed in the moving window of one year and shown in the Fig. 5.

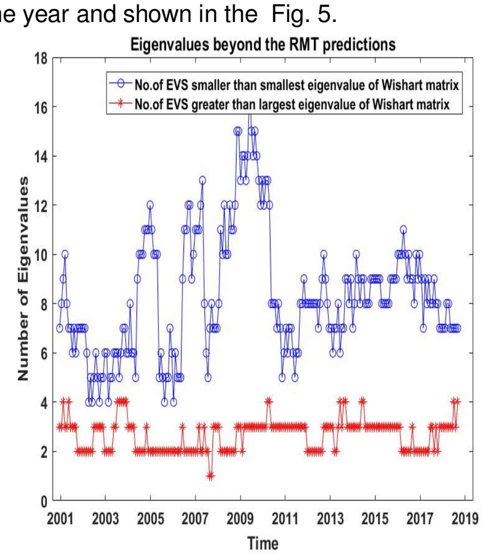

Fig. 5. Number of eigenvalues greater than RMT upper bound (blue curve) and number of eigenvalues smaller than lower bound of RMT predictions (red curve).

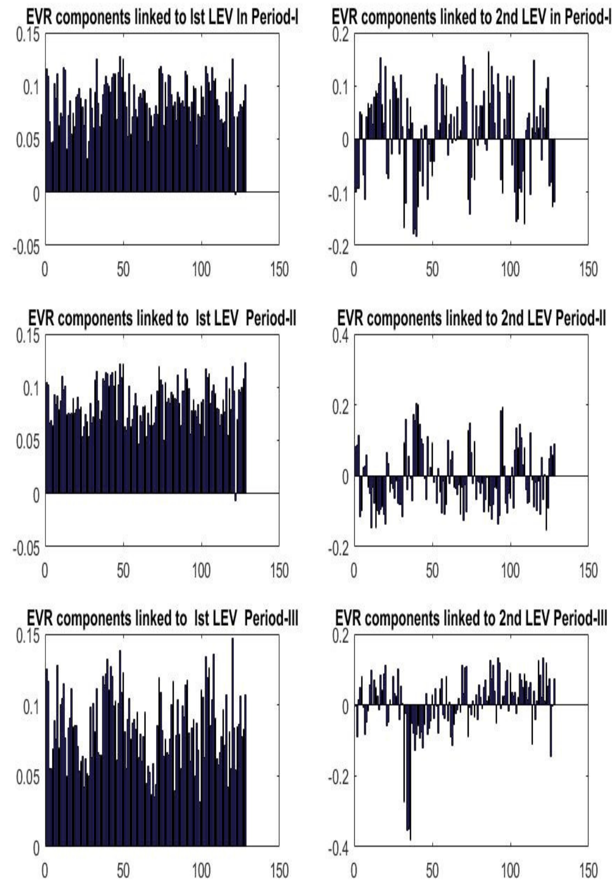

Fig. 6. Eigenvectors associated with first and second largest eigenvalues of correlation matrices in different periods of crisis.

We have calculated the Inverse Participation Ratio (IPR) in different periods of crisis. IPR delivers information linked to the involvement of component/stocks in the eigenvalue. The IPR [29] is defined as

$$I^k \equiv \sum_{l=1}^{m} [v_k^l]^4$$

where v_k^l , l=1,…,m are the elements of eigenvector u_k. In the computation of IPR we consider those elements of the eigenvector which have dominantly contributed in the eigenvalue. The reciprocal of number of such elements give the value of IPR.

The IPR in pre, during and post crisis period is shown with different colours in Fig.7.We found variation in the contribution of components/stocks during the different period of crisis of 2008.

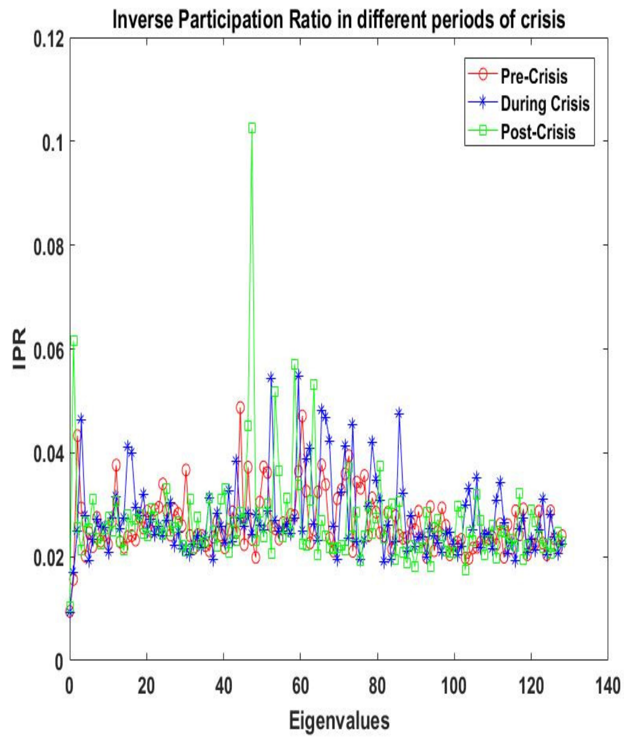

Fig. 7. Inverse Participation Ratio in pre, during and post crisis period.

B. Construction of correlation networks

To get information regarding the topology of the DJIA stocks network, we have constructed correlation networks from correlation matrices. The 128 stocks of S&P 500 index form the nodes of the network and correlation among them are the links connecting them. The data investigated in this work include the daily closing price of S&P 500 stocks. The time series of 12 years is divided into 139 overlapping time windows of width 250 trading days. In each time epoch, we construct the correlation network and calculate the average correlation coefficient. The time evolution of correlation coefficients is shown in Fig. 8.

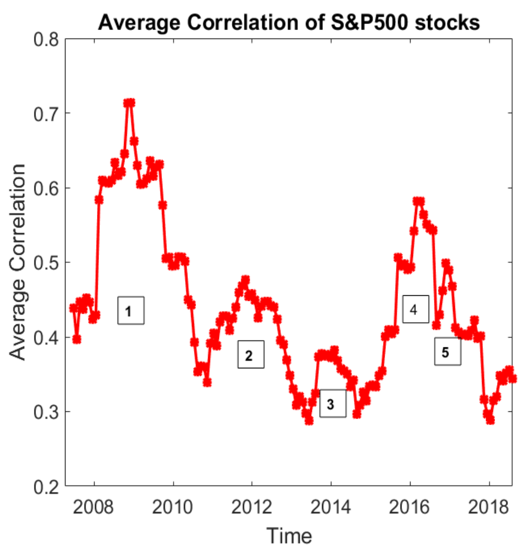

Fig. 8. Average correlation coefficient of S&P 500 stocks.

III. RESULTS AND DISCUSSION

From the RMT analysis, we found that time series of 128stocks of S&P 500 index investigated in this work contain useful information. The LEV of the cross correlation matrices lies outside the RMT predictions in all the periods of crisis. We also observe that LEV has significantly increased during the period of crisis. We find that number of EVS smaller than RMT predicted lower bound increases during the period of crisis as shown in Fig. 5. This is an indicator of systemic risk in the system, as the peak is observed during the period of crisis. The EVR associated with first largest eigenvalue showing the market mode as all the components are positive as shown in Fig.6. The contribution of eigenvalues to the Inverse participation ratio is different in different periods of crisis as shown in the Fig. 7. From Fig. 8 we have observed certain peaks in the average correlation curve. These peaks occurs in the periods 2008, 2012, 2014, 2016, Nov 2016 which corresponds to GFC08, European sovereign debt crisis, General Elections in India, Chinese Financial crisis and Demonetization period in India. So the changes in correlation have detected major extreme events in India and world. This study helps the investor to select the period for optimum profit.

IV. CONCLUSION

From the findings of the study we can conclude that the huge information is hidden in financial time series which is meaningless until transformed into useful information. The time series of S&P 500 stocks has economic importance. The largest eigenvalue has increased around 21% which is a significant increase. The average correlation increases during the period of financial crises. So we conclude that rise in volatility, increase in LEV, Increase in number of eigenvalues less than lower bound of RMT predictions and increase in correlation act as indicators of systemic risk in financial systems.

V. FUTURE SCOPE

In the present work we focussed on the static properties of the networks. There are enormous imminent works that can directly outgrow from the present research work.The correlation matrices constructed in present work can be filtered using power mapping technique. The eigenvalues within RMT predictions mainly signify noise and have negligible meaning. The eigenvalues beyond the Wishart matrix lower and upper bounds have structural implications, and represent collections of correlated stocks. Any empirical CCM (C_{corr}) can be represented as summation of two matrices, one matrix (C_{ran}) have random portion which includes all EVS fall within RMT bounds and second matrix (C_{st}) have EVS more than LEV of Wishart matrix. The structured portion (C_{st}) of CCM have the LEV of empirical CCM which represent the market mode. The EVS excluding the LEV of empirical CCM corresponds to mesoscopic clusters. The stocks in the mesoscopic clusters have same dynamics. These mesoscopic clusters is also called Group mode and can be analysed to extract more precise information. In present work we have considered only the network and their properties only in the static periods. We have not studied the time evolution of these networks and dynamic topological properties. So investigation of the evolution of networks may be further scope of work. To investigate the dynamic properties of the network of financial indices, we had to compute the dynamic correlation among the stocks. Moving time window of suitable length is considered and it is shifted through a time epoch

Conflict of Interest: No

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