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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 United States. We have studied the time series of 128 stocks of S&P500 index of India. We have considered three durations in the time series as pre-crisis, during crisis 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, Financial crisis, 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, 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; CD, Consumer discretionary; FIN, Financials; HEA, Healthcare; IND, Industrials; IT, Information Technology; MAT, Materials; UTI, Utilities.

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 [1-3]. 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 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 important in the field of Econophysics.

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 understanding the 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 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 among stocks [2, 10, 25-34]. RMT was originally established in 1951 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 (Wishart Matrix) with EVD of the Cross Correlation Matrix (CCM) constructed from empirical time series. In RMT approach, the deviations of eigenvalues of CCM (obtained from empirical time series) 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 among the dominant indices of global stock markets. Zheng *et al.* [42] have observed direct connection between variations in correlation and occurrence of booms, bubbles and crises.

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 United States using CBN. Onnela *et al.* [52] have investigated New York Stock Exchange (NYSE) using CBN. Tumminello et al [53] have used PMFG to investigate topology of NYSE. In our previous study [54] we have studied the stability of Sensex index of BSE and Nifty50 index of NSE. 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 find little systematic work where impact of different extreme or critical events on the Indian stock market has been investigated.

In the present work we have studied the structure and dynamics of network of 128 stocks of S&P 500 index of India. The S&P 500 index is leading stock market index of Indian Stock Market(ISM). This index covers around 96% of market capitalization. Around 93% of the total turnover on National Stock Exchange (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 time series of 128 dominant stocks of S&P 500 index of India. The daily closing price of 128 stocks 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 128 stocks of S&P500 index is plotted in the Fig.1.The GFC08 erupted in the United States and then spread to the all the countries around the globe. To study the impact of GFC08 on the ISM, we consider 3 sub-periods [34]. 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 extract the hidden information from time series of 128 stocks of S&P 500 index.

Table 1: List of 128 stocks of S&P 500 index of India studied.

S. No.	Abbre.	Full Name	Sector	S.N	Abbre.	Full Name	Sector
1	TTMT	TATA Motors Ltd	CD	65	GLXO	GlaxoSmithKline Phamaceuticals Ltd	HEA
2	MM	Mahindra and Mahindra Ltd	CD	66	APHS	Apollo Hospitals	HEA
3	HMCL	Hero MotoCorp Ltd	CD	67	PIEL	Piramal Enterprises Limites	HEA
4	BOS	Bosch Ltd	CD	68	TRP	Torrent Pharmaceuticals Ltd	HEA
5	MSS	MothersonSumi Systems Ltd	CD	69	IPCA	IPCA Labs Ltd	HEA
6	TTAN	Titan Company Ltd	CD	70	SANL	Sanofi India Limted	HEA
7	Z	Zee Entertainment Private Ltd	CD	71	PFIZ	Pfizer Ltd	HEA
8	BHFC	Bharat Forge Company Ltd	CD	72	NTCPH	NATCO Pharmaceuticals Ltd	HEA
9	EXID	Exide Indus Ltd	CD	73	LT	Larsen and Toubro Ltd	IND
10	APTY	Apollo Tyres Ltd	CD	74	BHEL	Bharat Heavy Electricals Ltd	IND
11	MRF	MRF Ltd	CD	75	SIEM	Siemens Ltd	IND
12	IH	Indian Hotels Company Ltd	CD	76	CCRI	Container Corp. of India	IND
13	BATA	Bata India Ltd	CD	77	ABB	ABB India Ltd	IND
14	BIL	Balkrishna Industries Ltd	CD	78	EIM	Eicher Motors Ltd	IND
15	EIH	EIH Ltd	CD	79	KKC	Cummins India Ltd	IND
16	WHIRL	Whirlpool of India Ltd	CD	80	BHE	Bharat Electronics Ltd	IND
17	TC	Thomas Cook Ltd	CD	81	HAVL	Havells India Ltd	IND
18	SF	Sundram Fasteners Ltd	CD	82	GDSP	Godrej Industries Private Ltd	IND
19	BBTC	Bombay Burmah Trading Corp. Ltd.	CD	83	ENGR	Engineers India Ltd	IND
20	KRB	KRBL Ltd.	CD	84	AMRJ	Amara Raja Batteries Ltd	IND
21	ITC	ITC Ltd	CD	85	VOLT	Voltas Ltd	IND
22	HUVR	Hindustan Unilever Ltd	CS	86	SKF	SKF India Ltd	IND
23	DABUR	Dabur India Ltd	CS	87	3M	3M India Ltd	IND
24	CLGT	Colgate Palmolive	CS	88	FNXC	Finolex Cables Ltd	IND
25	SKB	GlaxoSmithKline	CS	89	GRIL	Graphite India Ltd	IND
26	MRCO	Marico Ltd	CS	90	ESC	Escorts Ltd	IND
27	PG	Procter and Gamble Ltd	CS	91	AL	ashokaleyland ltd	IND
28	BRIT	Britannia Industries Ltd	CS	92	HEG	HEG ltd	IND
29	TGBL	TATA Global Beverages Ltd	CS	93	SCHFL	Schaeffler India Ltd.	IND
30	GILL	Gillette India Ltd	CS	94	INFO	Infosys Ltd	IT
31	AISG	Asahi India Glass Ltd	CS	95	WPRO	WIPRO Ltd	IT
32	ONGC	Oil and Natural Gas Corp. of India	CS	96	MPHL	Mphasis Ltd	IT
33	RIL	Reliance Industries Ltd	EN	97	HEXW	Hexaware Technologies Ltd	IT
34	IOCL	Indian Oil Corp. Ltd	EN	98	HWA	Honeywell Automation India Ltd	IT
35	BPCL	Bharat Petroleum Corp. Ltd	EN	99	CYL	Cyient Ltd	IT
36	HPCL	Hindustan Petroleum Corp. Ltd	EN	100	TELX	TATA Elexsi Ltd	IT
37	MRPL	Mangalore Refinery and Petrochemicals Ltd	EN	101	HZ	Hindustan Zinc Ltd	MAT
38	HDFCB	Great Eastern Shipping Company Ltd	EN	102	APNT	Asian Paints Ltd	MAT
39	SBIN	Gujarat Mineral Development Corp. Ltd	FIN	103	TATA	TATA Steel Ltd	MAT
40	ICICIBC	ABAN Offshore Ltd	FIN	104	SAIL	Steel Authority of India Ltd	MAT

41	HDFC	HDFC Bank Ltd	FIN	105	HNDL	Hindalco Industries Ltd	MAT
42	AXSB	Axis Bank Ltd	FIN	106	ACEM	Ambuja Cements Ltd	MAT
43	KMB	Kotak Mahindra Bank Ltd	FIN	107	GRASIM	Grasim Industries Ltd	MAT
44	BOB	Bank of Baroda	FIN	108	JSTL	Jindal Steel and Power Ltd	MAT
45	IIB	IndusInd Bank Ltd	FIN	109	ACC	ACC Ltd	MAT
46	SHTF	Shriram Transport Finance Ltd	FIN	110	SRCM	Shree Cement Ltd	MAT
47	BOI	Bank of India	FIN	111	PIDI	Pidilite Industries Ltd	MAT
48	IDBI	IDBI Bank Ltd	FIN	112	CSTRL	Castrol India Ltd	MAT
49	LICHF	LIC Housing Finance Ltd	FIN	113	NACL	National Aluminium Company Ltd	MAT
50	RCAPT	Reliance Capital Ltd	FIN	114	UPLL	UPL Ltd	MAT
51	BJHI	Bajaj Holdings and Investment Ltd	FIN	115	BRGR	Berger Paints Ltd	MAT
52	CRISIL	Crisil Ltd	FIN	116	TTCH	TATA Chemicals Ltd	MAT
53	BAF	Bajaj Finance Ltd	FIN	117	KNPL	KansalNerolac Paints Limted	MAT
54	FB	Federal Bank Ltd	FIN	118	TRCL	Ramco Cements Ltd	MAT
55	GRHF	Gruh Finance Ltd	FIN	119	SI	Supreme Industries Ltd	MAT
56	CIFC	Cholamandalam Investment and Finance Company Ltd	FIN	120	CENT	Century Textiles and Industries Ltd	MAT
57	DEWH	Dewan Housing Finance Corp. Ltd	FIN	121	GFLC	Gujarat Fluorochemicals Ltd	MAT
58	CUBK	City Union Bank	FIN	122	PI	PI Industries Ltd	MAT
59	JM	JM Financial Ltd	FIN	123	BASF	BASF India Ltd	MAT
60	SUNP	Sun Pharmaceutical Industries Ltd	FIN	124	ATLP	Atul Ltd	MAT
61	LPC	Lupin Ltd	HEA	125	VEDL	vedanta ltd	MAT
62	DRRD	Dr. Reddy's Laboratories Ltd	HEA	126	GAIL	GAIL India Ltd	UTI
63	CIPLA	CIPLA Ltd	HEA	127	TPWR	TATA Power Company Ltd	UTI
64	ARBP	Aurobindo Pharmaceuticals Ltd	HEA	128	RELI	Reliance Infrastructure Ltd	UTI

Abbreviation Used: CD, Consumer discretionary; FIN, Financials; HEA, Healthcare; IND, Industrials; IT, Information Technology; MAT, Materials; UTI, Utilities;

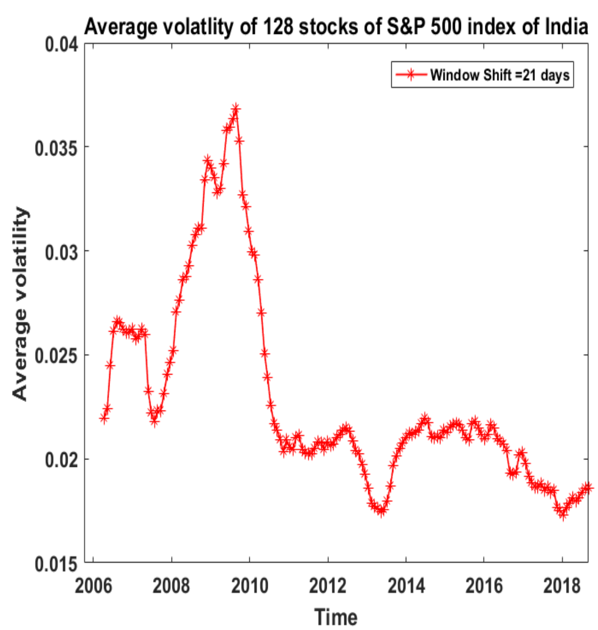

Fig. 1. Average volatility of 128 stocks of S&P 500 index of India.

A. Random Matrix Theory

In RMT approach [31-36], 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 128 stocks of S&P 500 index is constructed as follows: Let $PR_k(\tau)$ denote the daily closing prices of the stock 'k' at time (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 ⟨…⟩ represent the time average over the period of study.

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

$$Corr_{km} \equiv \langle NL_k(\tau) NL_m(\tau)\rangle$$

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 L ($m \to \infty, L \to \infty$) with ratio $\gamma = \frac{L}{m} \geq 1$, the probability distribution ($P_{rand}(\eta)$) of eigenvalues (η) of Wishart matrix which follows Marchenko-Pastur distribution is given by,

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

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

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

For a random data, all the eigenvalues of CCM fall in the limits $[\eta_{min}, \eta_{max}]$. Any deviation from this bound indicate the presence of economic information in time series. The probability distribution of the eigenvalues of cross-correlation matrices of 128 stocks of S&P 500 index and probability distribution of eigenvalues of Wishart matrix in pre, during and post-crisis periods are shown in the Fig. 2, Fig. 3 and Fig. 4 respectively.

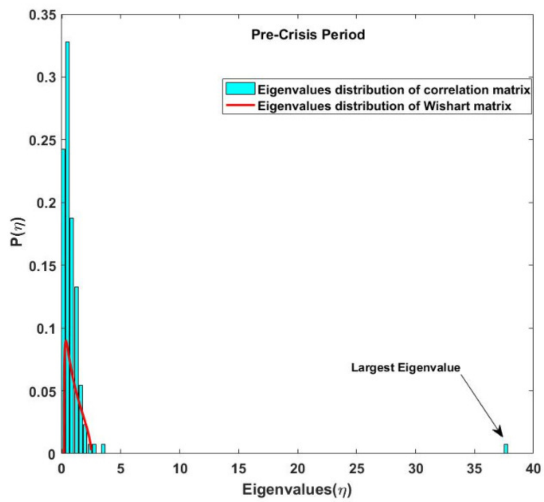

Fig. 2. Probability distribution of eigenvalues of correlation matrix of 128 stocks of S&P 500 and eigenvalues of Wishart matrix in pre-crisis period

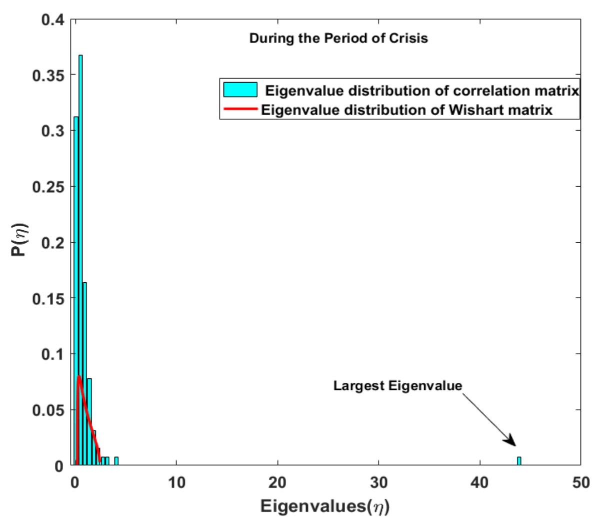

Fig. 3. Probability distribution of eigenvalues of correlation matrix of 128 stocks of S&P 500 index and eigenvalues of Wishart matrix during the period of crisis.

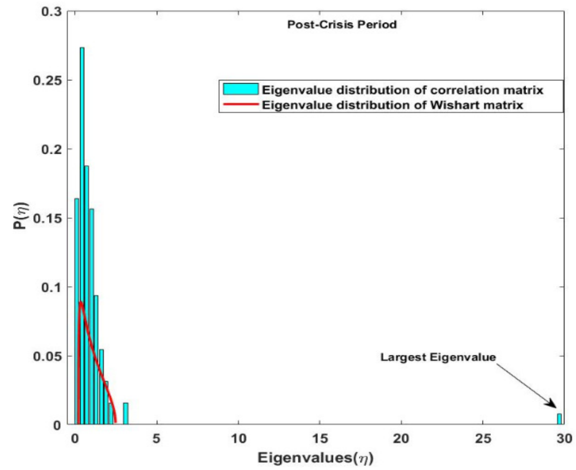

Fig. 4. Probability distribution of eigenvalues of correlation matrix of 128 stocks of S&P 500 index and eigenvalues of Wishart matrix in post-crisis period.

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

Table 2: RMT results for 128 stocks of S&P 500 index of India.

Eigenvalues	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

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 represents the market mode and gives the collective dynamics of the stocks. The second largest eigenvalue provide the information related to sector or cluster formation among the stocks of S&P 500 index. The first and second largest eigenvalues are outside RMT bounds (η_{min}, η_{max} 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 plotted in the Fig. 5.

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 eigenvector associated with second largest EVS provide clustering information. The components of EVR (U_k) corresponding to Ist and 2nd LEV in the pre, during and post-crisis periods are in shown in the Fig. 6.

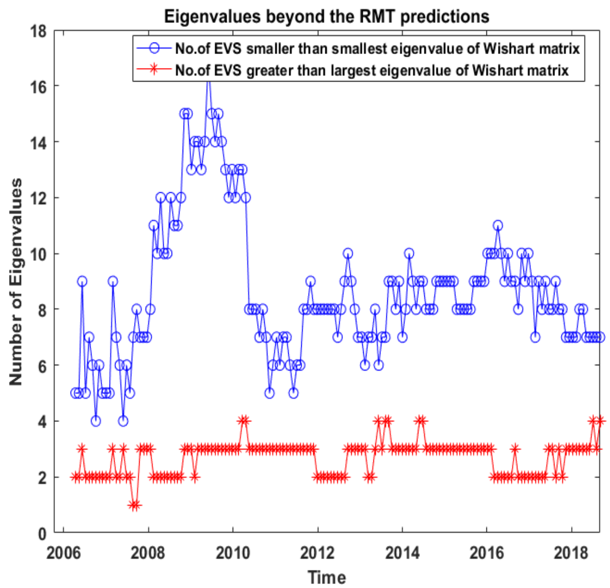

Fig. 5. Number of eigenvalues greater than RMT upper bound (red colour) and number of eigenvalues smaller than lower bound of RMT predictions (blue colour).

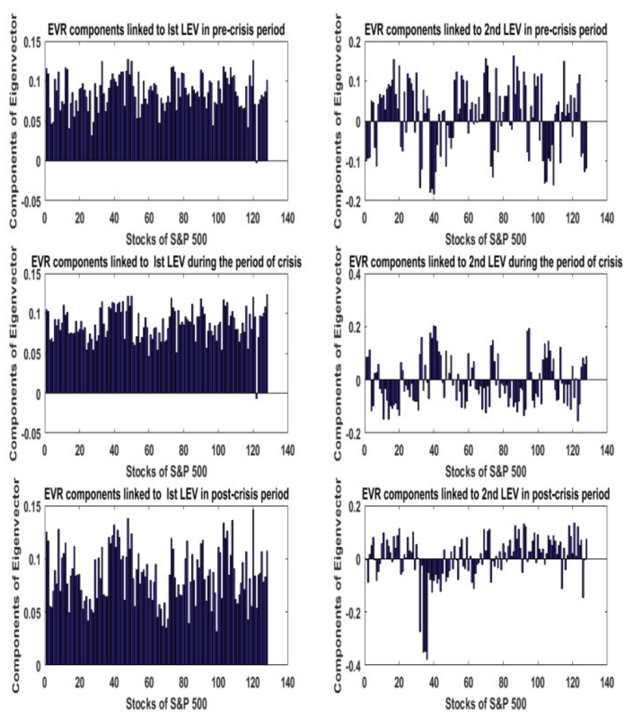

Fig. 6. Components of eigenvectors associated with first and second largest eigenvalues of correlation matrices in different periods of crisis.

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=1,2…m are the elements of eigenvector(v_k).

In the computation of IPR, we consider those elements of the eigenvector which have dominantly contributed in the eigenvalues. 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.

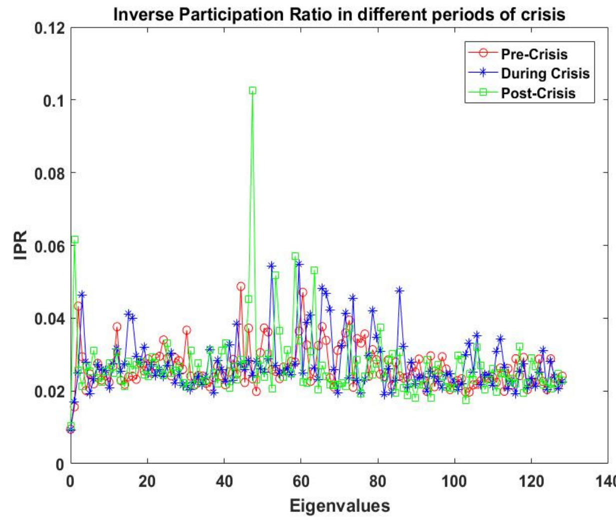

Fig. 7. Inverse Participation Ratio in pre, during and post crisis period.

B. Construction of correlation networks

To get information regarding the topology of the 128 stocks of S&P 500 index, 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 120 stocks of S&P500 index. The time series of stocks from 2006 to 2018 is divided into 155 overlapping time windows of width 250 trading days (approx. one year). 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.

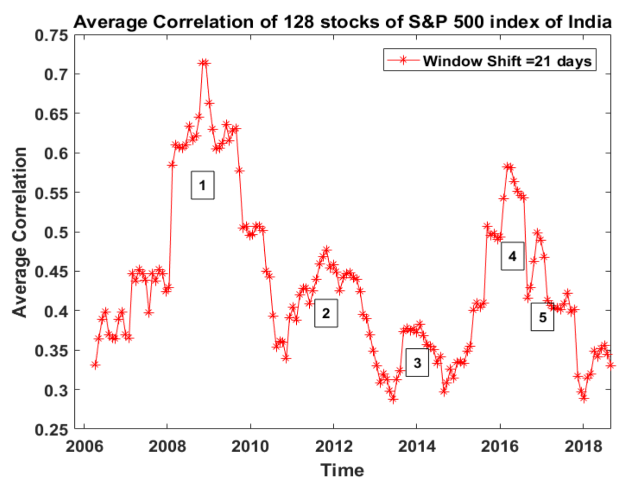

Fig. 8. Average correlation coefficient of 128 stocks of S&P 500 index of India. Peaks number with corresponding time periods are: 1(2008), 2(2012), 3(2014), 4(2016), 5(November, 2016).

III. RESULTS AND DISCUSSION

We found increase in the volatility of the 128 stocks of S&P 500 index during the period of crisis (GFC08) as shown in Fig. 1. From RMT analysis, we found that time series of 128 stocks of S&P500 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 as shown in the Fig. 2, Fig. 3 and Fig. 4. We have found that LEV has increased significantly during the period of crisis. The Fig. 5 shows increase in the number of EVS smaller than RMT predicted lower bound during the period of crisis. This is an indicator of systemic risk in the system, as a 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. We have found certain peaks in the average correlation graph as shown in Fig. 8. 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.

IV. CONCLUSION

From this investigation, 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 128 stocks of S&P 500 index has important economic importance. The largest eigenvalue has increased around 21% which is a significant increase. Peaks are observed in the average correlation graph which corresponds to the period of extreme events. 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 have focused 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 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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