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Topological Properties of Network of Global Currency Exchange Rates

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***Abstract**: We study time series of exchange rates of 37 global currencies expressed in terms of US dollars. We take US dollar is as the base currency because it is one of dominant currencies, which is used almost in 66 countries as their currency. The average volatility is computed from returns using overlapped rolling window technique. To study the effects of crisis on the structure and dynamics, we consider three sub periods; before crisis, during crisis and after crisis. Different statistical properties and network properties in three sub periods. From analysis of currency network at different thresholds, we find change in the structure of network in the period of crisis. We find the highly correlated and weakly correlated currencies in the calm and crisis period using threshold networks, which can help the investors in portfolio management. The group of most correlated currencies in the crisis period is different from that in before and after crisis period. Different centrality measures can differentiate the currencies according to their geographical location.*

***Keywords :**Econophysics, correlation, random matrix theory, threshold networks, centralities measures*

I. INTRODUCTION

Recently financial markets have been studied extensively using approaches based on physics and mathematics tools. Following the global financial crisis of 2008, stability of stock markets has attracted huge attention. The global financial crisis of 2008 erupted in United States and affected the economies of many countries. Many different methods have been used to understand the structure of the stock markets [1-10]. The weighted networks linking different elements within the system have been used to study many complex systems like financial market, gene regulation, food webs and many more. In these weighted networks, each interacting element is the node of network and correlation between the interacting elements is the link between nodes. Kumar and Deo [11] have used the correlation based threshold networks to study the topological properties of global financial indices. They have applied RMT to investigate network properties. He and Deem [12] analysed the network of world trade. They have studied the effects of globalization and recessions on network structure. Onnella et al. [13] have observed the structural changes in the network of financial systems during the period of crisis by using correlation network techniques. Vandewalle et al. [14] have analysed 6358 US stocks using minimum spanning tree. They have studied topological properties using hierarchical techniques. Qiu et al. [15] have studied the dynamic behaviour of American and Chinese markets using static and dynamic thresholds. Namaki et al. [16] have applied the random matrix approach to the Dow Jones Industrial Average (DJIA). They have used filtered correlation matrices to study the topological properties of Tehran Stock Exchange (TSE) at different thresholds. Huang et al. [17] have investigated the Chinese stock market using threshold network analysis and found that network of the stock market follow power law. Kantar et al [18] have analysed the 50 Turkish companies using MST and hierarchical techniques. They have observed that global financial crisis of 2008 have not much affected the Turkey's companies. Eryigit and Eryigit [19] have investigated the properties of hundreds of stocks of different countries. They have found that East Asian countries were weakly connected while North American and European markets were strongly connected. Zheng et al. [20] have analysed the worldwide finance and commodities markets using hierarchical techniques. They have constructed modified MST using absolute values of correlation coefficients as metric distances.

In our previous work [21], we have studied the stability of Indian stock market using diffusion entropy. We have considered the time series of dominant indexes of Indian stock market i.e BSE Sensex and NSE Nifty50 and analysed their stability in the context of global financial crisis of 2008. In this work, we analyse daily data global currency exchange rates using complex network approach and hierarchical techniques. We use the daily data of 37 countries currency exchange rates to calculate the return and to compute the correlation coefficients. The organization of paper is follows: in section-II, we discuss the data which is analysed in present work. We discuss the methodology used in the analysis; Threshold networks and hierarchical clustering techniques in section-III.

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In section IV we discuss the topological properties of the networks. The results are discussed in the section-V. In section-VI, summary of the findings is represented.

II. DATA ANALYZED AND METHODOLOGY

The times series of 37 global currency exchange rates in US Dollar (USD is considered as the base currency) is taken from the Bloomberg terminal in the LalBahadurShastri Institute of Management, New Delhi. The global currencies used in the analysis are listed in Table-1. We have computed the volatility which is a measure of market fluctuations as shown in Fig.1. We have filtered and divided the data into three distinct periods of crisis. Three different periods of crisis are considered as; before crisis, during crisis and after crisis similar to the periods considered for the analysis of global financial indices by kumar and Deo [11].

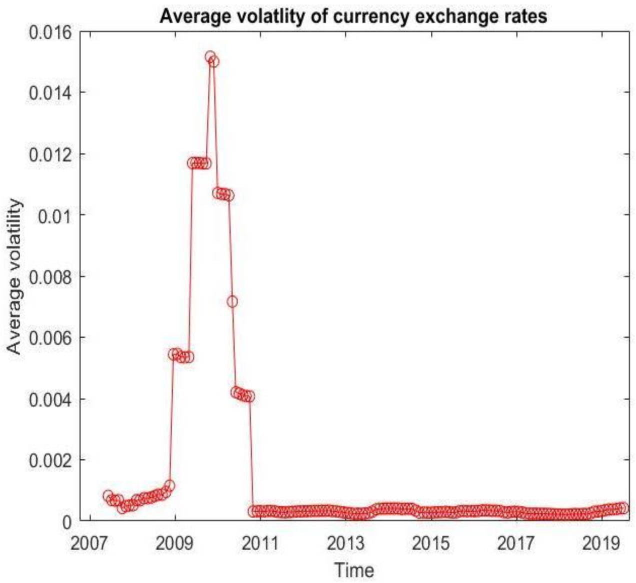

Fig.1: Average volatility of the global currency exchange rates computed for moving time window of one year

A. Random Matrix Theory Analysis (RMT)

Let $E_i(\tau)$ denote the daily closing value of exchange rate of currency 'i' in terms of USD at time τ. The logarithmic returns $R_i(\tau)$[11]are defined as

$$R_i(t) \equiv \ln E_i(\tau) - \ln E_i(\tau-1)$$

Then the normalized returns for the stock 'i' is defined as $NR_i(\tau) = \frac{R_i(\tau)-\langle R_i\rangle}{\sqrt{\langle R_i^2\rangle-\langle R_i\rangle^2}}$, where $\sigma_i = \sqrt{\langle R_i^2\rangle - \langle R_i\rangle^2}$ is the standard deviation of R_i and $\langle\ldots\rangle$ represents the time mean over the span of period.

The correlation matrix is computed using the normalized returns, having elements $C_{ij} \equiv < r_i(\tau) r_j(\tau) >$ lying in the range [-1, 1]. The Wishart matrix from random time series of the same length as that of empirical time series is generated and its eigenvalue distribution is compared with the cross-correlation matrix of empirical data. In the limiting values of N and T (n→ ∞, T → ∞) with ratio $X = \frac{T}{N} \geq 1$, the probability distribution of eigenvalues (ζ) of Wishart matrix[22,23] is $P(\lambda) = \frac{X}{2\pi}\frac{\sqrt{(\zeta_+-\zeta)(\zeta-\zeta_-)}}{\zeta}$,where maximum/minimum eigenvalues (ζ_+ and ζ_-) are $\zeta_\pm = \left[1 \pm \left(\frac{1}{\sqrt{X}}\right)\right]^2$.

The eigenvalues within the range $\zeta_+ \leq \zeta \leq \zeta_-$ i.e. RMT predictions represent the random behaviour of the time series and does not have economic meaning, whereas the eigenvalues beyond the RMT predictions have profound information.

Table-I: Currency exchange rates of 37 currencies in US Dollars (USD)

S.No	Acronym	Desription	Region
1	SGD	Singapore Dollar	Asia
2	PHP	Philippine Peso	Asia
3	KRW	South Korea Won	Asia
4	JPY	Japnese Yen	Asia
5	INR	Indian Rupee	Asia
6	IDR	Indonesian Rupiah	Asia
7	HKD	Hong kong Dollar	Asia
8	CNY	Chinese Yuan Renminbi	Asia
9	SYP	Syrian pound	Asia
10	SAR	Saudi Arabian riyal	Asia
11	QAR	Qatari Riyal	Asia
12	OMR	Omani Rial	Asia
13	LBP	Lebanese Pound	Asia
14	KWD	Kuwaiti Dinar	Asia
15	JOD	Jordanian Dinar	Asia
16	IRR	Iranian Rial	Asia
17	ILS	Israeli New Shekel	Asia
18	BHD	Bahraini Dinar	Asia
19	AED	UAE Dirham	Asia
20	UAH	Ukrainian Hryvnia	Europe
21	TRY	Turkish lira	Europe
22	RUB	Russian Ruble	Europe
23	RON	Romanian leu	Europe
24	PLN	Polish Zloty	Europe
25	ISK	Icelandic krona	Europe
26	HUF	Hungarian forint	Europe
27	CZK	Czech koruna	Europe
28	BGN	Bulgarian lev	Europe
29	PEN	Peruvian Sol	America
30	MXN	Mexican Peso	America
31	COP	Colombian Peso	America
32	CLP	Chilean Peso	America
33	BRL	Brazilian Real	America
34	ARS	Argentine peso	America
35	ZAR	South African Rand	Africa
36	MAD	Moroccan Dirham	Africa
37	EGP	Egyptian Pound	Africa

The statistics of eigenvalues of correlation matrices in different periods of crisis are listed in Table-II

Table-II: RMT results for currency exchange rates

Eigen values	Wishart matrix	Empirical correlation matrix		
		Pre crisis	During crisis	after crisis
Largest	1.6212	11.984	17.629	12.405
Smallest	0.5282	0.0902	0.0496	0.1295

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B. Random Matrix theory and correlation filtering

In the correlation filtering, we first calculate all the eigenvalues of the correlation matrix and the eigenvalues falling within RMT predictions are thrown out.

The eigenvalues coming out in the RMT predictions are due to randomness, so we have cleaned the data by setting all these eigenvalues (lying in the RMT predictions) equal to zero. The cross correlation matrix is reconstructed.Statistics of eigenvalues of correlation matrix and color map (Original & RMT filtered) of 37 global currency exchange rates before, during and after the crisis is shown in the Fig.2.

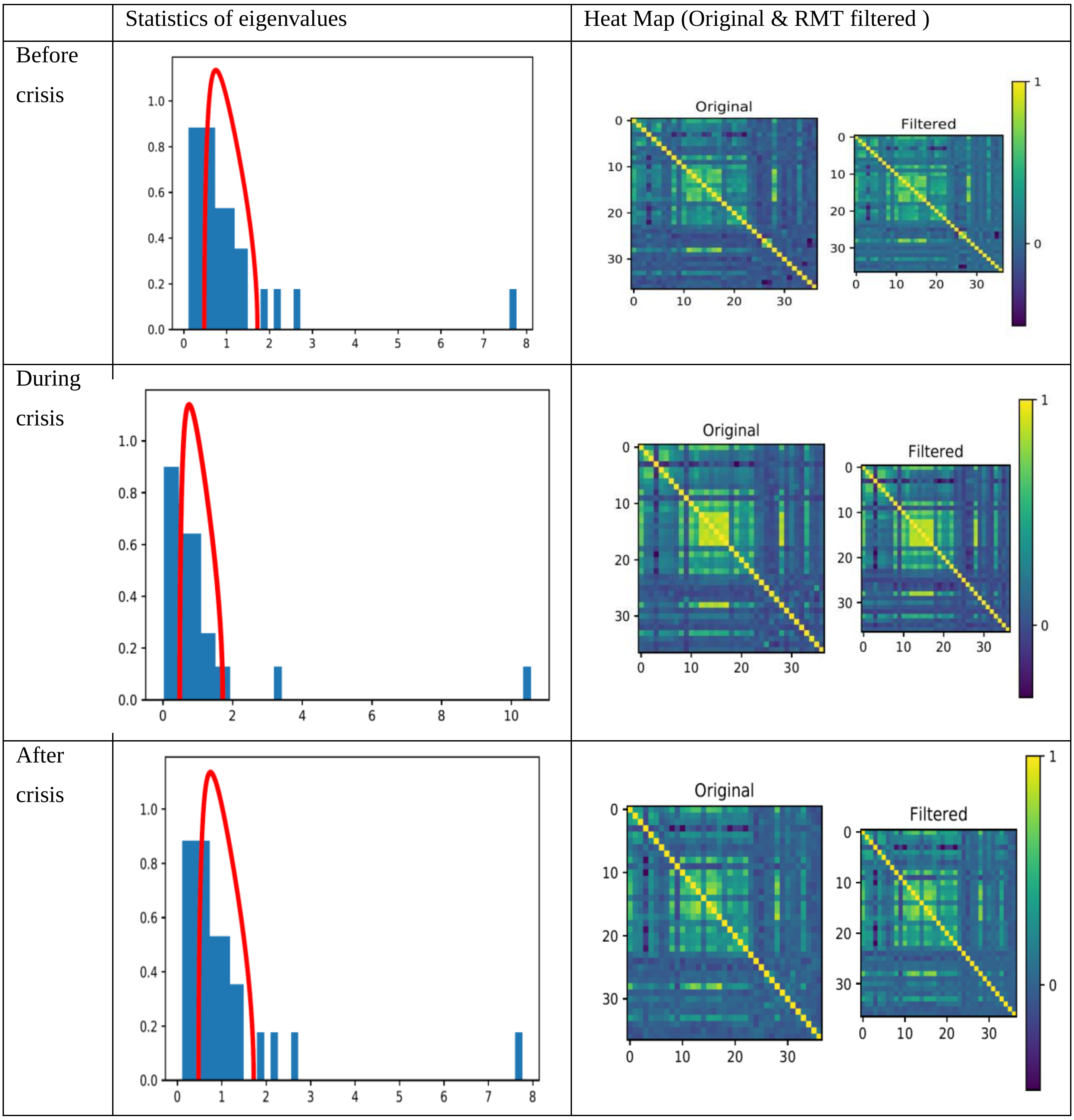

Fig.2: Statistics of eigenvalues of correlation matrix and color map (Original & RMT filtered data) of 37 global currency exchange rates before, during and after the crisis

III. Analysis of Currency Exchange Rates Using Complex Network Approach

Let the currency exchange rates denote the nodes (N_x) of the network. The value of correlation coefficients is the links which join the nodes. So the network is weighted undirected network based on correlation among currencies. At zero threshold, all the nodes are connected with the remaining nodes. To construct threshold network, we fix a threshold value 'θ' lying between -1 to 1 such that connection between nodes j and k is removed if $C_{jk}$is less than θ. The links (L) in the network are network of currency exchange rates are defined by

$$L = \begin{cases} l_{jk} = 1 \;\; if \; j \neq k \quad and \; C_{jk} \geq \theta \\ l_{jk} = 0 \;\; if \; j = k \end{cases}$$

We have constructed correlation networks of global currency exchange rates at different thresholds in different periods as shown in the Fig.3, Fig.4 and Fig.5 respectively.

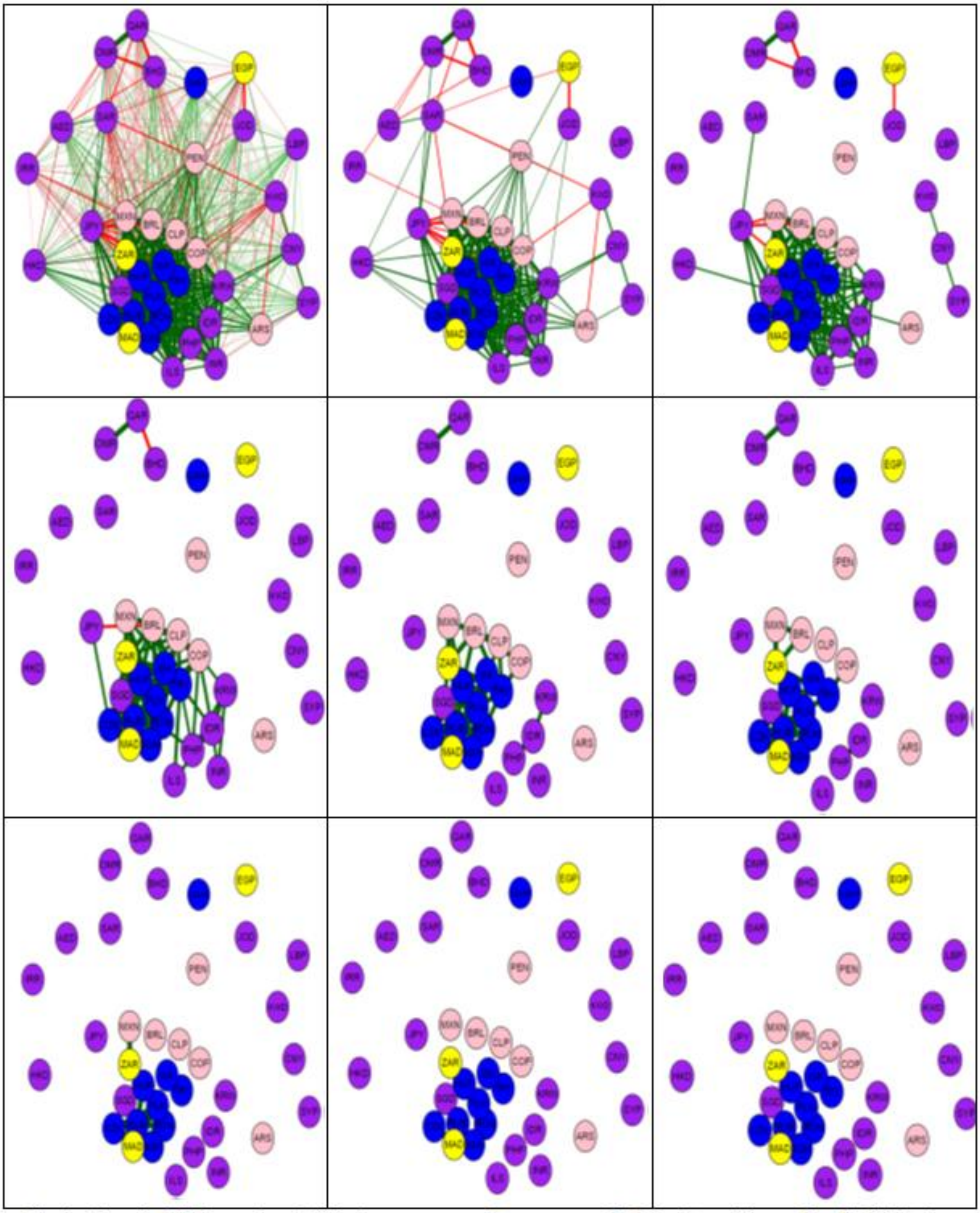

Fig.3: Threshold Network of global currency exchange rates before the crisis at thresholds 0.0 to 0.8(left to right)

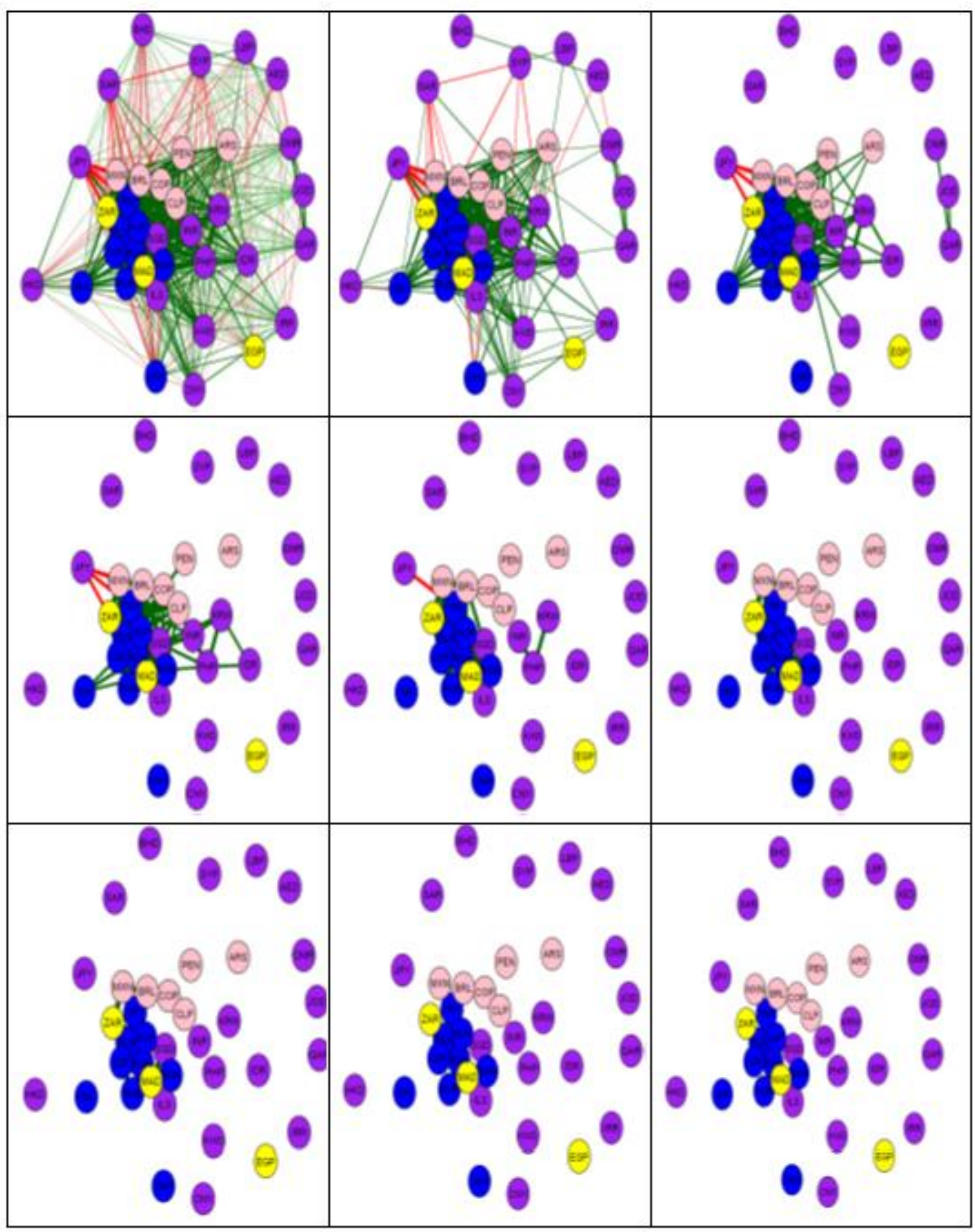

Fig.4: Threshold Network of global currency exchange rates during the crisis at thresholds 0.0 to 0.8(left to right)

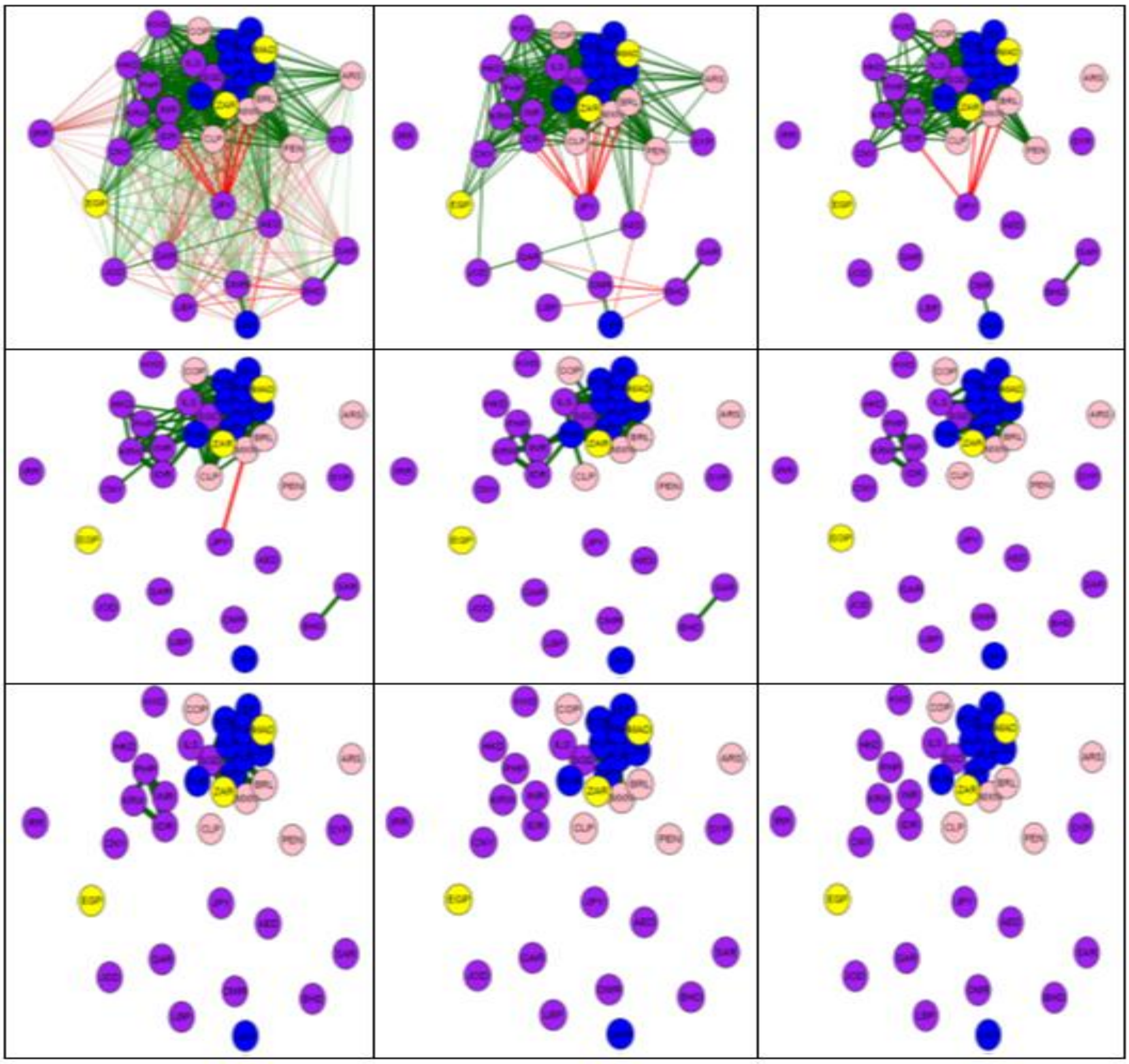

Fig.5: Threshold Network of global currency exchange rates after the crisis at thresholds 0.0 to 0.8(left to right)

IV. TOPOLOGICAL PROPERTIES OF NETWORK OF GLOBAL CURRENCYEXCHANGE RATES

***Mean degree*:** The mean degree of node *k* is numbermany neighbours a node in the network has on average. This measure can be calculated only when the network has at least one edge connecting the nodes. In the correlation network of financial indices, a large value of the degree indicates that it is correlated with many other indices. Degree of the different currencies is calculated in Table-III.

***Clustering coefficient*:** If D_i are the nearest neighbours of vertex '*i*' have 'm_i, edges among them, the ratio of m_i to $\frac{D_i(D_i-1)}{2}$ is the clustering coefficient of vertex *i*. The global clustering coefficient is simply the ratio of triangles and connected triples in the correlation network of financial indices. The calculated clustering coefficients of the different currencies are shown in the Table-IV.

Centrality: Centrality indicates prominence of a node. It captures node with high prominence / structural importance / critical position / popularity. Higher the value of centrality, higher is the prominence of node in the graph. Node Centrality Measures can be classified on the basis of degree and flow. The degree based centralities consider the count of neighbours and various degree based centralities are degree centrality and Eigen vector centrality etc.Flow based Centrality includes Eccentricity centrality, Closeness Centrality, Decay Centrality, Betweeness Centrality and Spanning tree Centrality.

Degree Centrality is defined as $DC\ (V_i) = d_i$, where $d_i$is the degree of nodeV_i.Normalized Degree Centrality is defined as $NDC\ (V_i) = \frac{d_i}{N-1}$, where N is the order of G. Degree based Centralities do not consider topology of entire network. Higher the degree, higher is the importance of node. Degree centrality are used to identifying influential actors in social networks, finding top trading companies in economic networks, hubs in computer networks and identifying super spreaders in epidemics.

Closeness Centrality: Extends degree centrality by looking at neighbourhoods of all sizes.

ItCaptures closeness with rest of the nodes in the graph. High closeness centrality, implies high approachability of the node from rest of network.

Betweenness Centrality: Considers how many shortest paths passes through the node.High betweenness centrality means high control on information. Betweenness centrality is used in capturing bridging connection, controlling information flow in the network , positioning of server and scheduling its maintenance activities in the communication network , Positioning of junction in the transportation Network etc.Topmost ten Currencies in the order decreasing closeness and betweenness centrality before, during and after the crisis are listed in Table-V

Average Shortest Path length: The average shortest path length (ASPL)is given by $\frac{\sum\sum_{j>i} d(V_i,V_j)}{\binom{N}{2}}$.
The ASPL in the period before, during and after the crisis are 9.61285,8.86356 and 8.69435 respectively.

Table-III: Degree of the nodes (currencies) before, during and after the crisis

Before Crisis		During Crisis		After Crisis	
Curr	Degree	Curr	Degree	Curr	Degree
PLN	9.7086	HUF	10.44403	PLN	12.73036
HUF	9.233349	PLN	10.17017	HUF	12.28383
RON	9.023865	CZK	9.928005	SGD	12.23096
MAD	8.792006	MAD	9.833856	RON	11.95347
BGN	8.651112	RON	9.697276	BGN	11.85489
RUB	8.645538	SGD	9.360092	CZK	11.80425
TRY	8.380369	TRY	9.353199	TRY	11.63329
SGD	7.935002	BGN	9.144796	MAD	11.23239
ZAR	7.922465	ZAR	8.859939	ZAR	11.04318
CZK	7.615496	BRL	8.401783	ISK	10.86677
ISK	7.496389	RUB	8.093419	RUB	10.49723
BRL	7.058987	MXN	7.793227	MXN	10.44262
COP	6.799832	COP	7.102465	BRL	10.00369
CLP	6.566042	CLP	6.9101	ILS	9.694541
MXN	5.852846	ILS	6.647266	INR	7.929387
IDR	5.58844	INR	6.610573	IDR	7.437485
PHP	5.578307	PHP	5.966639	COP	7.181894
KRW	5.191074	KRW	5.207651	PHP	6.998501
ILS	5.144579	PEN	4.978263	CLP	6.926516
INR	4.469098	ISK	4.043565	KRW	6.574664
JPY	4.270716	JPY	3.826483	HKD	5.447295
PEN	3.080051	IDR	3.509862	KWD	4.949273
ARS	2.538994	KWD	3.123199	PEN	4.251599
SAR	2.294737	ARS	3.008269	CNY	4.138813
OMR	2.261697	CNY	2.385445	JPY	3.073767
QAR	2.117481	UAH	2.327878	AED	2.75324
BHD	2.038149	SAR	2.231725	SYP	2.617968
KWD	2.004487	OMR	1.948311	ARS	2.611775
JOD	1.973987	QAR	1.909159	EGP	2.32697
HKD	1.936682	JOD	1.908223	QAR	2.144955
CNY	1.882227	SYP	1.905132	OMR	1.908237
UAH	1.877054	IRR	1.876965	BHD	1.749564
EGP	1.732665	EGP	1.755696	JOD	1.726895
SYP	1.626509	HKD	1.656272	UAH	1.64779
IRR	1.363925	BHD	1.580512	LBP	1.615115
LBP	1.357387	LBP	1.264043	SAR	1.603564
AED	1.781578	AED	1.253411	IRR	1.183448

Table -IV: Clustering Coefficient of global currency exchange rates network before, during and after crisis

Clustering Coefficient							
Currency	Before Crisis	During Crisis	After Crisis	Currency	Before Crisis	During Crisis	After Crisis
SGD	0.48253968	0.58412698	0.59047619	**MXN**	0.32380952	0.48253968	0.558730159
PHP	0.38730159	0.48888889	0.558730159	**COP**	0.59047619	0.45079365	0.679365079
KRW	0.47619048	0.55873016	0.66031746	**CLP**	0.59047619	0.53333333	0.641269841
JPY	0.01904762	0.22857143	0.177777778	**BRL**	0.53968254	0.54603175	0.501587302
INR	0.36825397	0.46984127	0.571428571	**ARS**	0.25396825	0.27301587	0.196825397
IDR	0.38095238	0.53333333	0.653968254	**SYP**	0.1015873	0.0952381	0.444444444
HKD	0.1968254	0	0.641269841	**SAR**	0.17142857	0.07619048	0.177777778
CNY	0.3047619	0.32380952	0.603174603	**QAR**	0.04444444	0.19047619	0.031746032

ZAR	0.54603175	0.55238095	0.577777778	**OMR**	0.03174603	0.36190476	-0.012698413
UAH	0.25396825	0.1015873	0.006349206	**MAD**	0.59047619	0.50793651	0.60952381
TRY	0.57777778	0.6031746	0.533333333	**LBP**	0.22222222	0.01269841	0.101587302
RUB	0.52698413	0.50793651	0.60952381	**KWD**	0.13968254	0.41269841	0.520634921
RON	0.54603175	0.55238095	0.565079365	**JOD**	0.12063492	0.23492063	0.247619048
PLN	0.56507937	0.50793651	0.66031746	**IRR**	0.19047619	0.22857143	0.431746032
ISK	0.51428571	0.4	0.565079365	**ILS**	0.36825397	0.59047619	0.546031746
HUF	0.57777778	0.53968254	0.66031746	**EGP**	0.18412698	0.05714286	0.374603175
CZK	0.56507937	0.53333333	0.615873016	**BHD**	-0.03809524	0.15238095	-0.012698413
BGN	0.53968254	0.52063492	0.565079365	**AED**	0.13333333	0.08888889	0.380952381
PEN	0.46984127	0.46984127	0.603174603				

Table-V: Topmost 10 Currencies in the order of closeness and betweenness centrality before, during and after the crisis

Betweenness Centrality					
Before Crisis		During Crisis		After Crisis	
TRY	2.68353651	SGD	4.58140994	SGD	4.77825473
HUF	1.97177413	TRY	2.05397916	ILS	1.6220104
COP	1.97177413	KRW	1.61821523	IDR	1.57626773
PLN	1.67520648	BGN	1.13887491	PEN	0.75289965
BGN	1.55657942	PHP	0.65953459	CNY	0.70715697
KRW	0.96344411	HUF	0.48522902	KWD	0.52418629
JPY	0.96344411	BRL	0.48522902	KRW	0.38695827
SGD	0.90413058	COP	0.44165263	MXN	0.38695827
MXN	0.84481705	CLP	0.09304149	MAD	0.24973026
ZAR	0.54824939	MXN	0.04946509	TRY	0.20398759
Closeness Centrality					
Before Crisis		During Crisis		After Crisis	
PLN	1.3651596	SGD	1.31115825	SGD	1.28225224
TRY	1.23951388	HUF	1.23159954	RUB	1.09729083
HUF	1.21456868	PLN	1.20440439	ILS	1.07918677
RON	1.14188774	RON	1.1820878	PLN	1.0730635
ZAR	1.09335608	CZK	1.16960454	HUF	1.03416046
BGN	1.07357342	TRY	1.15008111	TRY	0.99401463
RUB	1.05482466	MAD	1.1169878	CZK	0.94806509
MAD	0.99906804	BGN	1.0835179	ZAR	0.93435677
SGD	0.96074727	ZAR	0.93678946	BGN	0.89683382
COP	0.90839863	BRL	0.87051604	RON	0.89574617

V. RESULT AND DISCUSSION

In the present work of analyzing the currency exchange rates of 37 currencies, we have constructed the correlation matrix (CM) of the returns. The calculated largest and smallest eigen values of CM are out of bound of Wishart matrix (i.e. RMT predictions), which shows that the interaction in the global currency exchange rates is not random but contains important information. The eigen values of the cross correlation matrix which lies in range of RMT predictions are due to randomness, so we have cleaned the data by setting all such eigenvalues equal to zero and reconstructed the cross correlation matrix. Heat maps and probability distribution is shown in the Fig.II for the original and filtered correlation matrix in different periods of crisis.

To get more insight information threshold networks are constructed at different thresholds (θ) as shown in the Fig.3 to Fig.5.In the threshold networks green color of edge shows correlation between the currencies and red color shows the anti-correlation among the currencies. More is the thickness of the edge, more is the correlation. At small threshold (θ =0.2), IRR, AED and LBP currencies disconnected from the network showing that they are weakly correlated in all periods of the crisis. At very high threshold (θ =0.8), MAD, BGN, CZK, PLN remain connected indicating that they are strongly correlated currencies.

Analyzing the threshold networks at a threshold of 0.6 it can be concluded that European currencies form a strongly correlated cluster among all periods of crisis.

In the section IV, we have calculated the topological properties average degree, clustering coefficient, centrality and ASPL of the network. These topological properties are listed in the tables from Table-III-Table-V. We find decrease in ASPL of network during and after crisis showing closeness in nodes in these periods. The degree centrality of different currencies is listed in the Table-III. The currencies PLN, HUF, RON, MAD, ZAR, BGN, TRY, SGD, and CZK have high degree centrality. The degree centrality of these currencies increases during and after the crisis.

The clustering coefficients of the currencies before, during and after the crisis are calculated and listed in the Table -IV. The TRY and COP are highly clustered currencies in different periods of crisis. The clustering coefficients of the currencies SGD, PHP, KRW, INR, IDR, CNY, KWD, JOD, IRR (Asian countries) increases during and after the crisis. The clustering coefficients of the currencies JPY, TRY, RUB, PLN, ISK, HUF, CZK, BGN, COP, CLP, BRL, QAR,QMR,MAD ILS,AED and SYP decreases during the crisis and increases after the crisis. The clustering coefficients of the currencies UAH, LBP decreases during and after the crisis.

We have calculated the closeness and betweenness centrality of the currencies in different periods of crisis. SGD currency has highest closeness and betweenness centrality during and after the crisis. Few currencies having high closeness and betweenness centrality are listed in the Table -V. The currencies PLN, SGD,BGN,TRY,ZAR,RON AND HUF have high closeness in all periods of crisis, while currencies SGD,TRY,KRW and MXN have high betweenness in all periods of crisis

VI. CONCLUSION

The RMT analysis of the currency exchange rates of 37 countries revealed that interaction in the global currency exchange rates is not but contains important information since the calculated largest and smallest eigen values are out of bound of Wishart matrix. The threshold networks shows that IRR, AED and LBP currencies are weakly connected in the network in all periods of the crisis and MAD, BGN, CZK, PLN currencies are strongly connected. Analysis of the threshold networks at high threshold showed that European currencies form a strongly correlated cluster among all periods of crisis.The average shortest path length decreases during and after the crisis showing the nodes (currencies) come closer during and after the crisis. The currencies PLN, HUF, RON, MAD, ZAR, BGN, TRY, SGD, and CZK have high degree centrality. The degree centrality of these currencies increases during and after the crisis. The TRY and COP currencies are highly clustered currencies in different periods of crisis. The clustering coefficients of the currencies UAH, LBP decreases during and after the crisis.SGD currency has highest closeness and betweenness centrality during and after the crisis.

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