Chapter 11
Uncovering the Network Structure of the World Currency Market: Cross-Correlations in the Fluctuations of Daily Exchange Rates

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Abstract The cross-correlations between the exchange rate fluctuations of 74 currencies over the period 1995–2012 are analyzed in this paper. The eigenvalue distribution of the cross-correlation matrix exhibits a bulk which approximately matches the bounds predicted from random matrices constructed using mutually uncorrelated time-series. However, a few large eigenvalues deviating from the bulk contain important information about the global market mode as well as important clusters of strongly interacting currencies. We reconstruct the network structure of the world currency market by using two different graph representation techniques, after filtering out the effects of global or market-wide signals on the one hand and random effects on the other. The two networks reveal complementary insights about the major motive forces of the global economy, including the identification of a group of potentially fast growing economies whose development trajectory may affect the global economy in the future as profoundly as the rise of India and China has affected it in the past decades.

11.1 Introduction

At whatever scale one studies economic phenomena, we can find complex systems, comprising relatively large number of mutually interacting elements often connected to each other in non-trivial topologies, at work. The components can be individual traders, firms, banks, markets or countries, but however complicated the behavior of the individual agents in the system, an even richer collective behavior is manifested at the scale of the entire group of interacting agents. Explaining the emergence of such systems-level phenomena which may be qualitatively different from the properties exhibited by the individual components is one of the key goals of many physicists working on socio-economic questions, an enterprise that is of-

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F. Abergel et al. (eds.), *Econophysics of Agent-Based models*,
New Economic Windows, DOI 10.1007/978-3-319-00023-7_11,

ten referred to as *econophysics* [1]. An important step in this direction will be to identify features of economic systems that are *universal*, in the sense of occurring at many different scales, suggesting that their existence is not contingent upon the particular conditions prevailing in a specific situation. This will help econophysicists to focus on phenomena that are not just the outcome of a series of historical accidents and which can therefore be potentially explained by generalizable mechanisms.

Market dynamics has been identified by many physicists as a particular area of economics that has the potential for yielding several such universal features. In particular, one can mention the identification of scale-invariant distributions in price fluctuations, the trading volume and number of trades [2, 3] in equities markets (but see also Ref. [4]). However, in order to get an understanding of how qualitatively new features emerge at the level of the collective dynamics of the entire market, one needs to understand the nature and structure of interactions between the agents. While several studies on the networks underlying equities markets (e.g., Ref. [5]) have been done, we need to compare between markets of different kinds in order to distinguish those features that are particular to specific systems and those which are universal. With this aim, we undertake a detailed investigation of the world currency market in this article. While several previous studies have looked at the cross-correlations between the foreign exchange rates of different currencies (e.g., see Refs. [7–9]), our results reveal several novel insights and unexpected features of the network of interactions between the currencies that we reconstruct from the cross-correlations data. The period of the preceding sixteen years we have chosen for our study has seen remarkable transformations in the world economy with the emergence of new economic powerhouses such as China and India, but it has also shown how our world is vulnerable to massive system-spanning crises (such as that of 2007–2008). The study of networks in the global currency market provides an important perspective with which to view the positive as well negative impacts of globalization. It has been argued that globalization is neither a completely new phenomenon in world history nor are its effects always beneficial to the economy [10]. We hope that by investigating the collective dynamics of the international trade in currencies in order to identify the major motive forces of the world economy, one can potentially understand the long-term trends and prospects of globalization.

11.2 The World Currency Market

The foreign exchange (FX) market, representing the entire global decentralized trading of various currencies, is the largest financial market in the world with an average daily trading volume estimated in 2010 to be 4×10^{12} US Dollars [11]. A typical trade in the FX market consists of a pair of agents exchanging a certain amount of a particular currency for a mutually agreed amount of another currency. The ratio of the amounts of the two currencies changing hands specify the corresponding *exchange rate* for the pair of currencies concerned. Thus the exchange rates determine the value of a currency with respect to another (the numeraire). The modern FX market characterized by a large number of currencies having floating exchange rates which continuously fluctuate over time date from the 1970s. The varying rates reflect the changing demand and supply for the currencies, and are thought to be directly influenced by the trade deficit/surplus of the corresponding countries [12] as well as macroeconomic variables such as changes in growth of the gross domestic product, interest rates, etc. However, international events can often trigger large perturbations in the FX market and it is possible that sudden changes in the exchange rates of a certain group of currencies can spread over time, eventually affecting a much larger number of currencies. Our article aims at uncovering the network of interactions between the different currencies of the FX market along which perturbations can propagate in the world currency market.

Description of the data set. We have considered the daily exchange rate of currencies in terms of US Dollars (i.e., the base currency) publicly available from the website of the financial services provider company, Oanda Corporation [13]. We have chosen the US Dollar as the numeraire as it is currently the primary reserve currency of the world and is most widely used in international transactions. The daily rates are computed as the average of all exchange rates (taken as the midpoint of the bid and ask rates) quoted during a 24-hour period prior to the day of posting the rate. For cross-correlation analysis, we have focused on the price data of $N = 74$ currencies from October 23, 1995 to April 30, 2012, which corresponds to $T = 6034$ working days. The choice of currencies was governed by our decision to only include those which either follow a free float or a managed float exchange rate regime. We have thus avoided currencies such as the Chinese yuan whose rate of exchange is pegged against another currency so that the value of currency does not vary appreciably in time (resulting in trivial cross-correlations). We have also excluded countries having a dollarized economy such as Panama, Ecuador Vietnam or Zimbabwe, that use a foreign currency—in majority of cases, the US Dollar—instead of or alongside the domestic currency, as this introduces strong artifacts in the cross-correlations. The period of observation was chosen so as to maximize the volume of available data. Using the MSCI Market Classification Framework [14] we have divided the countries to which the currencies belong into three categories: developed, emerging and frontier markets. This classification is based on a number of criteria including market accessibility, size and liquidity of the market and the sustainability of economic development. While many of the OECD countries belong to the developed category, the rapidly growing economies of Asia, Africa and Latin America (such as the BRICS group comprising Brazil, Russia, India, China and South Africa) are in the emerging category with the frontier markets category being populated by the remainder. The individual currencies, along with the above economic classification of the corresponding countries and the geographical regions to which they belong are given in Table 11.1.

Table 11.1 The list of 74 currencies analyzed in this article arranged according to type of market and grouped by geographical region

i	Currency code	Currency name	Type of market	Geographical region
1	CAD	Canadian Dollar	Developed	Americas
2	DKK	Danish Krone	Developed	Europe and Middle-East
3	EUR	Euro	Developed	Europe and Middle-East
4	ILS	Israeli New Shekel	Developed	Europe and Middle East
5	ISK	Iceland Krona	Developed	Europe and Middle-East
6	NOK	Norwegian Kroner	Developed	Europe and Middle-East
7	SEK	Swedish Krona	Developed	Europe and Middle-East
8	CHF	Swiss Franc	Developed	Europe and Middle-East
9	GBP	Great Britain Pound	Developed	Europe and Middle-East
10	AUD	Australian Dollar	Developed	Asia-Pacific
11	HKD	Hong Kong Dollar	Developed	Asia-Pacific
12	JPY	Japanese Yen	Developed	Asia-Pacific
13	NZD	New Zealand Dollar	Developed	Asia-Pacific
14	SGD	Singapore Dollar	Developed	Asia-Pacific
15	BOB	Bolivian Boliviano	Emerging	Americas
16	BRL	Brazilian Real	Emerging	Americas
17	CLP	Chilean Peso	Emerging	Americas
18	COP	Colombian Peso	Emerging	Americas
19	DOP	Dominican Republic Peso	Emerging	Americas
20	MXN	Mexican Peso	Emerging	Americas
21	PEN	Peruvian Nuevo Sol	Emerging	Americas
22	VEB	Venezuelan Bolivar	Emerging	Americas
23	ALL	Albanian Lek	Emerging	Europe, Middle-East and Africa
24	DZD	Algerian Dinar	Emerging	Europe, Middle-East and Africa
25	CVE	Cape Verde Escudo	Emerging	Europe, Middle-East and Africa
26	CZK	Czech Koruna	Emerging	Europe, Middle-East and Africa
27	EGP	Egyptian Pound	Emerging	Europe, Middle-East and Africa
28	ETB	Ethiopian Birr	Emerging	Europe, Middle-East and Africa
29	HUF	Hungarian Forint	Emerging	Europe, Middle-East and Africa
30	MUR	Mauritius Rupee	Emerging	Europe, Middle-East and Africa
31	MAD	Moroccan Dirham	Emerging	Europe, Middle-East and Africa
32	PLN	Polish Zloty	Emerging	Europe, Middle-East and Africa
33	RUB	Russian Rouble	Emerging	Europe, Middle-East and Africa
34	ZAR	South African Rand	Emerging	Europe, Middle-East and Africa
35	TZS	Tanzanian Shilling	Emerging	Europe, Middle-East and Africa
36	TRY	Turkish Lira	Emerging	Europe, Middle-East and Africa
37	INR	Indian Rupee	Emerging	Asia
38	IDR	Indonesian Rupiah	Emerging	Asia

Table 11.1 (Continued)

i	Currency code	Currency name	Type of market	Geographical region
39	KRW	South Korean Won	Emerging	Asia
40	PHP	Philippine Peso	Emerging	Asia
41	PGK	Papua New Guinea Kina	Emerging	Asia
42	TWD	Taiwan Dollar	Emerging	Asia
43	THB	Thai Baht	Emerging	Asia
44	GTQ	Guatemalan Quetzal	Frontier	Americas
45	HNL	Honduran Lempira	Frontier	Americas
46	JMD	Jamaican Dollar	Frontier	Americas
47	PYG	Paraguay Guarani	Frontier	Americas
48	TTD	Trinidad Tobago Dollar	Frontier	Americas
49	HRK	Croatian Kuna	Frontier	Europe and CIS
50	KZT	Kazakhstan Tenge	Frontier	Europe and CIS
51	LVL	Latvian Lats	Frontier	Europe and CIS
52	BWP	Botswana Pula	Frontier	Middle-East and Africa
53	KMF	Comoros Franc	Frontier	Middle-East and Africa
54	GMD	Gambian Dalasi	Frontier	Middle-East and Africa
55	GHC	Ghanaian Cedi	Frontier	Middle-East and Africa
56	GNF	Guinea Franc	Frontier	Middle-East and Africa
57	KES	Kenyan Shilling	Frontier	Middle-East and Africa
58	KWD	Kuwaiti Dinar	Frontier	Middle-East and Africa
59	MWK	Malawi Kwacha	Frontier	Middle-East and Africa
60	MRO	Mauritanian Ouguiya	Frontier	Middle-East and Africa
61	MZM	Mozambique Metical	Frontier	Middle-East and Africa
62	NGN	Nigerian Naira	Frontier	Middle-East and Africa
63	STD	Sao Tome and Principe Dobra	Frontier	Middle-East and Africa
64	SYP	Syrian Pound	Frontier	Middle-East and Africa
65	ZMK	Zambian Kwacha	Frontier	Middle-East and Africa
66	JOD	Jordanian Dinar	Frontier	Middle-East and Africa
67	BND	Brunei Dollar	Frontier	Asia
68	BDT	Bangladeshi Taka	Frontier	Asia
69	KHR	Cambodian Riel	Frontier	Asia
70	FJD	Fiji Dollar	Frontier	Asia
71	PKR	Pakistan Rupee	Frontier	Asia
72	WST	Samoan Tala	Frontier	Asia
73	LKP	Lao Kip	Frontier	Asia
74	LKR	Sri Lankan Rupee	Frontier	Asia

11.3 The Return Cross-Correlation Matrix

To quantify the degree of correlation between the exchange rate movements for different currencies, we first measure the fluctuations using the logarithmic return so that the result is independent of the scale of measurement. If $P_i(t)$ is the exchange rate of the i-th currency at time t (in terms of USD), then the logarithmic return is defined as

$$R_i(t, \Delta t) \equiv \ln P_i(t + \Delta t) - \ln P_i(t). \tag{11.1}$$

For daily return, $\Delta t = 1$ day. By dividing the time-series of returns thus obtained with their standard deviation (which is a measure of the volatility of the currency exchange rate), $\sigma_i = \sqrt{\langle R_i^2 \rangle - \langle R_i \rangle^2}$, we obtain the normalized return, $r_i(t, \Delta t) \equiv R_i/\sigma_i$. We observed that the cumulative distribution of the returns displayed power-law scaling in the tails, i.e., $P(r_i > x) \sim x^{-\alpha}$ where α is the corresponding exponent value. Using maximum likelihood estimation, the exponents for the different currencies were obtained and they were found to be distributed over a narrow range of values with a peak around $\alpha \simeq 3$. This indicates that the so-called *inverse-cubic law* distribution of returns, reported in many studies of stock price fluctuations [15–18], also holds for currency exchange rate movements [19, 20]. This further strengthens the *universality* of this empirical fact about the nature of market fluctuations and supports the validity of explaining this feature using very general models which do not consider details of particular markets or economies (see, e.g., Ref. [21]).

After obtaining the return time series for all N currencies over the period of T days, we calculate the cross-correlation matrix $\mathbf{C}$ whose individual elements $C_{ij} = \langle r_i r_j \rangle$, represent the correlation between returns for a pair of currencies i and j. If the fluctuations of the different currencies are uncorrelated, the resulting random correlation matrix (referred to as a Wishart matrix) has eigenvalues distributed according to [22]:

$$P(\lambda) = \frac{Q}{2\pi} \frac{\sqrt{(\lambda_{max} - \lambda)(\lambda - \lambda_{min})}}{\lambda}, \tag{11.2}$$

with $N \to \infty$, $T \to \infty$ such that $Q = T/N \geq 1$. The bounds of the distribution are given by $\lambda_{max} = [1 + (1/\sqrt{Q})]^2$ and $\lambda_{min} = [1 - (1/\sqrt{Q})]^2$. For the data we have analyzed, $Q = 81.54$, which implies that in the absence of any correlation the spectral distribution should be bounded between $\lambda_{max} = 1.23$ and $\lambda_{min} = 0.79$. We observe from Fig. 11.1 that the bulk of the empirical eigenvalue distribution indeed falls below the upper bound given by λ_{max}, although a significant fraction of the eigenvalues are smaller than what we expect from the lower bound λ_{min}. Also, a small number ($\simeq 8$) of the largest eigenvalues are seen to deviate from the bulk of the distribution predicted by random matrix theory, and we focus our analysis on these modes to obtain an understanding of the interaction structure of the world currency market.

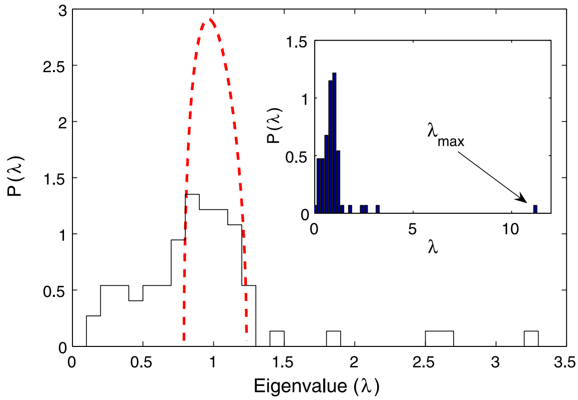

Fig. 11.1 The probability density function of the eigenvalues of the cross-correlation matrix **C** for fluctuations in the exchange rate in terms of US Dollars of 74 currencies for the period Oct 1995–April 2012. For comparison the theoretical distribution predicted by Eq. (11.2) is shown using *broken curves*. We explicitly verified that the theoretical distribution fits very well the spectral distribution of surrogate correlation matrices generated by randomly shuffling the returns for the different currencies. The *inset* shows the largest eigenvalue corresponding to the global mode of market dynamics

The random nature of the eigenvalues occurring in the bulk of the distribution is also indicated by the distribution of the corresponding eigenvector components. Note that, these components are normalized for each eigenvalue λ_j such that, $\sum_{i=1}^{N}[u_{ji}]^2 = N$, where u_{ji} is the i-th component of the jth eigenvector. For random matrices generated from uncorrelated time series, the distribution of the eigenvector components follows the Porter-Thomas distribution,

$$P(u) = \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{u^2}{2}\right]. \tag{11.3}$$

We have explicitly verified this form for the corresponding distribution of the random surrogate matrices obtained by shuffling the empirical return time series so that all correlations between the different currencies are destroyed. As seen from Fig. 11.2, it also approximately fits the distributions of the eigenvector components for the eigenvalues belonging to the bulk of the empirical spectral distribution. However, the eigenvectors of the largest eigenvalues (e.g., the largest eigenvalue λ_{max}, as shown in the inset) deviate quite significantly, indicating its non-random nature.

The largest eigenvalue λ_0 for the cross-correlation matrix is about 9 times larger than the upper bound of the random spectral distribution. While this is similar to the situation for cross-correlations of stock movements in financial markets (e.g., see Refs. [5, 6]), the corresponding eigenvector does not show a relatively uniform composition unlike the case in equities markets where almost all stocks contribute to this mode with all elements having the same sign. Instead, there is large variation in the relative contributions of the different components to the largest eigenmode, with those of four currencies (VEB, PYG, NGN, BND) having a different sign than the

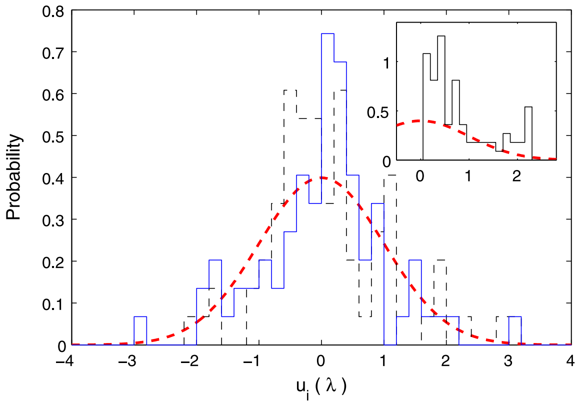

Fig. 11.2 The probability distribution of the eigenvector components corresponding to two eigenvalues belonging to the bulk of the spectral distribution predicted by random matrix theory and (*inset*) that corresponding to the largest eigenvalue. In both cases, the corresponding distribution obtained from the surrogate correlation matrices obtained by randomly shuffling the returns is shown using a broken curve for comparison

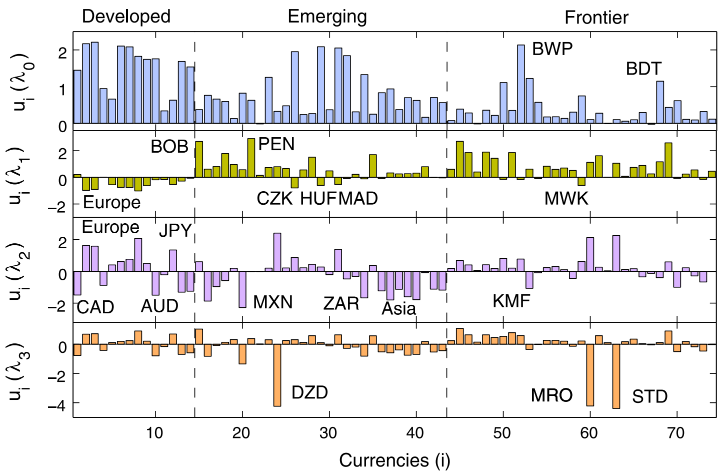

Fig. 11.3 The eigenvector components $u_i(\lambda)$ for the four largest eigenvalues of the correlation matrix **C**. The currencies are arranged according to the market classification of the corresponding country (developed, emerging or frontier) separated by *broken lines*. Some of the prominent components for each eigenvector (discussed in the text) are individually identified by the respective currency codes

rest—although with an extremely low magnitude (Fig. 11.3, top). This eigenmode represents the global component of the time-series of currency fluctuations which is common to all currencies. Thus, the strength of the relative contribution of a currency to the leading eigenvector can be construed as the extent to which the currency is in sync with the overall movement of the world currency market reflecting the collective response of the world economy to information shocks (which may include major perturbations such as the worldwide financial crisis of 2007–2008). Note that, this suggests that the relative strengths of the components in the leading eigenvector may be used as a measure of the role the corresponding currency plays in the world market (and to an extent, that the country plays in the international economy). Seen from this point of view, it is perhaps not surprising that most of the currencies belonging to countries in the developed markets category contribute significantly to this mode which reflects their dominance in the world economy. We also see that the countries in the emerging markets category can be very different from each other in terms of their role in the global mode, with components corresponding to the East European economies such as Czech Republic, Hungary and Poland having some of the largest contributions. Turning to the frontier markets category, while the contributions of most of these currencies have very low magnitude, a few countries (most notably Botswana but also Bangladesh, Kazakhstan and Comoros) stand out for the relatively high strength of the corresponding eigenvector component. The strong contribution from these countries could be either because of their impressive economic performance (e.g., Botswana has maintained one of the world's highest economic growth rates from the time of its independence in 1966 [23]) or possibly due to remittances in foreign currencies from expatriates working abroad having a large contribution to the national economy (as in the case of Bangladesh). As newly developing economies are potentially highly profitable but risky targets for foreign investment, it may be of interest to explore the possibility of using this measure to identify frontier markets having strong interaction with the world market which may make them relatively safer to invest in. On the other hand, from the point of view of portfolio diversification for reducing risk, one may use such a measure to identify economies whose fluctuations have the least in common with the global mode.

Of even more interest for understanding the topological structure of interactions in the world currency market are the intermediate eigenvalues in between the largest eigenvalue λ_0 and the bulk predicted by random matrix theory. For equities markets, it has been shown that in many cases the eigenvectors corresponding to these eigenvalues are localized, i.e., a relatively small number of stocks, usually having similar market capitalization or belonging to the same business sector, contribute significantly to these modes [6, 24, 25]. Figure 11.3 shows that the different currencies contribute to the different eigenvectors corresponding to the three largest intermediate eigenvalues very unequally. For example, from the eigenvector corresponding to λ_1, the second largest eigenvalue, we observe that many Latin American currencies such as those of Bolivia and Peru, have a dominant contribution in this mode with the contribution of European currencies (and a few non-European ones, such as those of Morocco and Malawi, whose economy is closely connected to that of Europe) being not only different but actually having the opposite sign. The third eigenvector shows that contributions from European and Japanese currencies have a different sign from that of established as well as rapidly developing economies of America, Asia-Pacific and Africa (such as Canada, Mexico, South Africa, Australia, New Zealand, Israel, Singapore and India). The fourth eigenvector has significant contributions from only three currencies, those of Algeria, Mauritania and Sao

Tome & Principe. This may reflect existing economic linkages between these countries that has resulted in such strong coupling in the movements of their currency exchange rates with respect to the US Dollar.

Despite the above insights, a direct inspection of eigenvector composition for the intermediate eigenvalues does not very often yield a straightforward interpretation of the group of currencies dominantly contributing to a particular mode. This is because apart from information about interactions between currencies, the cross-correlations are also affected strongly by the global mode corresponding to the overall market movement. In addition, there are a large number of modes belonging to the random bulk which correspond to idiosyncratic fluctuations. Both the global and random modes can mask significant intra-group correlations. Thus, in order to identify the topological structure of interactions between the currencies we need to remove the global mode corresponding to the largest eigenvalue and also filter out the effect of random noise (contributed by the eigenvalues belonging to the bulk of the spectral distribution). For this we use the filtering method proposed in Ref. [26] based on the expansion of a matrix in terms of its eigenvalues λ_i and the corresponding eigenvectors $\mathbf{u}_i$: $\mathbf{C} = \sum_i \lambda_i \mathbf{u}_i \mathbf{u}_i^T$. This allows the correlation matrix to be decomposed into three parts, corresponding to the global, group and random components:

$$\mathbf{C} = \mathbf{C}_{global} + \mathbf{C}_{group} + \mathbf{C}_{random} = \lambda_0 \mathbf{u}_0^T \mathbf{u}_0 + \sum_{i=1}^{N_g} \lambda_i \mathbf{u}_i^T \mathbf{u}_i + \sum_{i=N_g+1}^{N-1} \lambda_i \mathbf{u}_i^T \mathbf{u}_i, \quad (11.4)$$

where, the eigenvalues have been arranged in descending order (the largest labelled 0) and N_g is the number of intermediate eigenvalues. From the empirical data it may not be obvious what is the value of N_g, as the bulk may differ from the predictions of random matrix theory because of underlying structure induced correlations. For this reason, we use visual inspection to choose $N_g = 6$, and verify that small changes in this value do not alter the results. Our results are robust with respect to small variations in the estimation of N_g because the error involved is only due to the eigenvalues closest to the bulk that have the smallest contribution to $\mathbf{C}_{group}$. Figure 11.4 shows the result of the decomposition of the entire cross-correlation matrix (the distribution of whose elements is shown in the inset) into the three components. In contrast to the case of stock-stock correlations in financial markets (e.g., Ref. [6]), in the currency market the group correlation matrix elements C_{ij}^{group} show a significantly reduced tail and is completely enveloped by the distribution of the global correlation matrix elements C_{ij}^{global}. This indicates that there is a relatively small fraction of strongly interacting currencies, implying that the segregation into groups may be weak in this market.

In order to graphically present the interaction structure of the stocks using the information in the group correlation matrix $\mathbf{C}_{group}$, we first use a method suggested by Mantegna [27] to transform the correlation between currencies into distances to produce a connected network in which co-moving currencies are clustered together. The distance d_{ij} between two currencies i and j are calculated from the

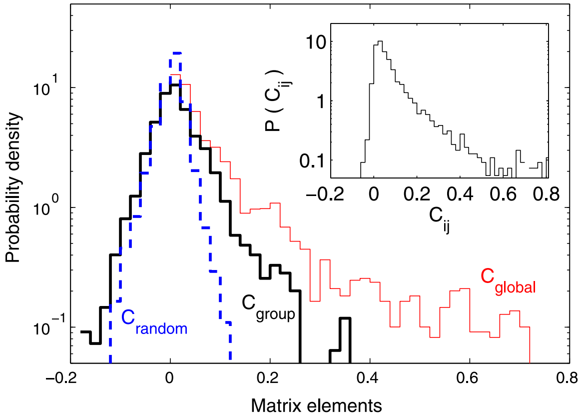

Fig. 11.4 The probability distribution of the matrix elements following decomposition of the correlation matrix **C** into global ($\mathbf{C}_{global}$), group ($\mathbf{C}_{group}$) and random effects ($\mathbf{C}_{effects}$) with $N_g = 7$. The distribution of the components C_{ij} of the original cross-correlation matrix **C** is shown in the inset for comparison

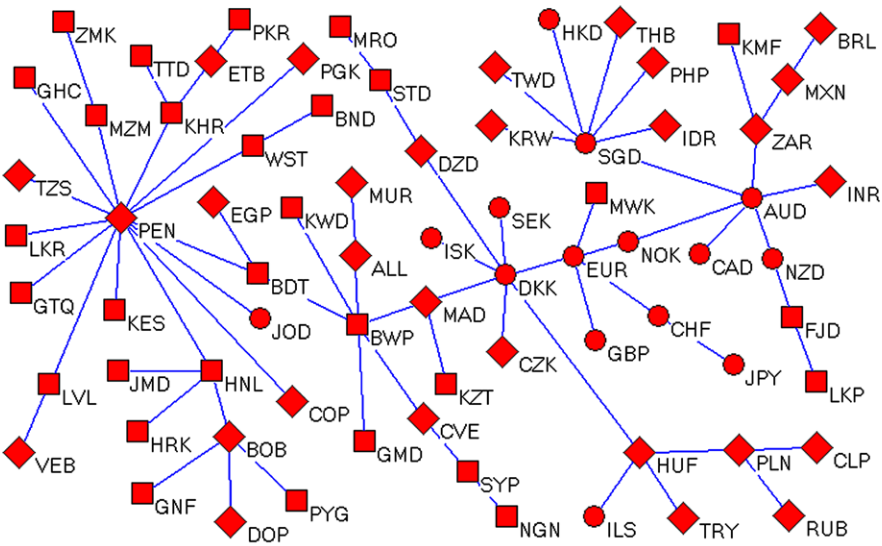

Fig. 11.5 The minimum spanning tree connecting the 74 currencies considered here. The node shapes indicate the type of the underlying economy of the country to which the currency belongs (*circles* indicate developed, *diamonds* indicates emerging and *squares* indicate frontier markets). The figure has been drawn using the Pajek software

cross-correlation matrix **C**, according to $d_{ij} = \sqrt{2(1 - C_{ij})}$. These are used to construct a minimum spanning tree, which connects all the N nodes of a network with $N - 1$ edges such that the total sum of the distance between every pair of nodes, $\sum_{i,j} d_{ij}$, is minimum. As seen in Fig. 11.5, for the currency market this method reveals clusters of currencies belonging to countries having similar economic profile and/or belonging to the same geographical region. In particular, note the cluster centered around the hub node (i.e., a node having significantly more connections than the average) corresponding to SGD which consists exclusively of currencies belonging to developed or emerging economies of the Asia-Pacific region such as those of Hong Kong, Taiwan, Thailand, Indonesia etc. On the other hand, the currencies clustered around the hub AUD are related by the geo-economic status of the corresponding countries of being major non-European players in the world economy (e.g., Canada, Mexico, Brazil, South Africa and India). It should be noted that the hubs of these two clusters (SGD and AUD) are directly linked to each other and are in turn connected to the cluster of European currencies (comprising two hubs corresponding to the Euro and the Danish currency) suggesting a close interplay in the currency movements of all the important countries driving international economic dynamics. Possibly more intriguing is the occurrence of a much bigger cluster (containing a third of all the currencies considered) arranged around the largest hub in the network which corresponds to the Peruvian currency. This cluster comprises a wide assortment of currencies belonging to countries spread geographically around the world but which share an economic resemblance in that most of them are in a relative state of underdevelopment compared to the economies considered earlier. It thus appears that the tree network representing the underlying interactions in the world currency market can be approximately divided into a part comprising developed or rapidly growing economies (dominated by Europe and Asia-Pacific) and another part composed of relatively underdeveloped ones (consisting mostly of Latin American and African countries), with the currency movements of these two groups being relatively independent of each other. Note that the two parts, in particular, the hubs corresponding to PEN and DKK, are bridged by the currencies of Morocco, Botswana and Bangladesh, which therefore have an importance in governing the collective dynamics of the world economy disproportionate to their intrinsic economic status. This can potentially explain the strong contribution of these currencies to the leading eigenvector of the cross-correlation matrix that represents the global eigenmode which has been discussed earlier in this article.

We have also used an alternative method of graph visualization in order to highlight any existing groups of currencies having significant mutual interactions. For the case of stocks in financial markets, the modules obtained by this technique often represent strongly performing business sectors in the economy [5, 6]. It is thus plausible that the currency communities identified using this method will represent important groupings driving the world economy. The binary-valued adjacency matrix $\mathbf{A}$ of the network is generated from $\mathbf{C}_{group}$ by using a threshold c_{th} such that $A_{ij} = 1$ if $C_{ij}^{sector} > c_{th}$, $A_{ij} = 0$ otherwise. An appropriate choice of the threshold makes apparent any clustering in the network that is implied by the existence of a tail in the C_{ij}^{group} distribution. Figure 11.6 shows the resultant network for the best choice of $c_{th} = c^*$ ($= 0.133$) in terms of creating the largest clusters of interacting currencies (isolated nodes have not been shown). The five clusters differ considerably in size, with two of them corresponding to strongly interacting currency triads (with the DZD-MRO-STD triad being the currencies having the dominant contribution to the fourth largest eigenmode identified earlier in Fig. 11.3). The next largest cluster, having nine currencies, consists of rapidly emerging economies outside Europe—including Brazil, India and South Africa of the BRICS group as well

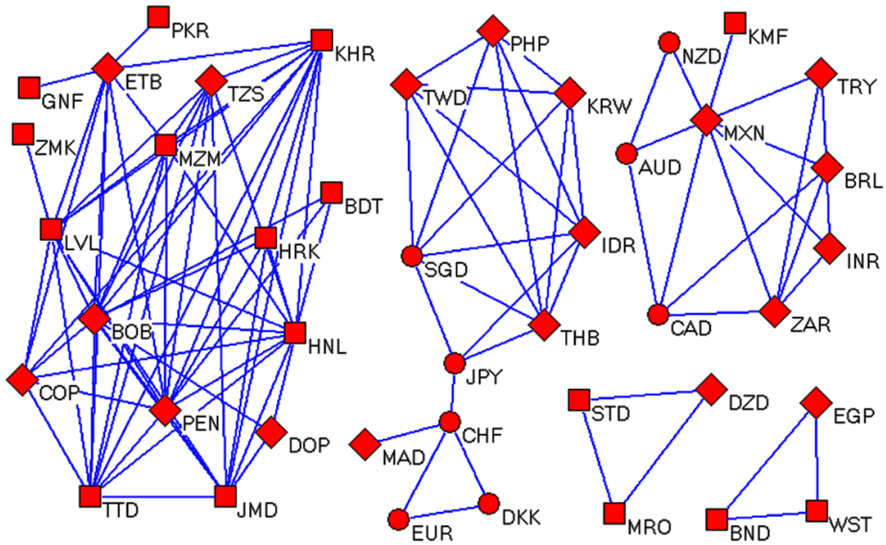

Fig. 11.6 The network of interactions among currencies generated from the group correlation matrix $\mathbf{C}_{group}$ with threshold $c^* = 0.133$. The node shapes indicate the type of the underlying economy of the country to which the currency belongs (*circles* indicate developed, *diamonds* indicates emerging and *squares* indicate frontier markets). The cluster at the center consists mostly of countries belonging to the Asia-Pacific region including several members of the ASEAN group, although it is also connected via the Japanese Yen to a smaller sub-group of European currencies. The cluster at top right consists of three of the BRICS countries as well as several economies outside Europe which are important in the global economy (such as Australia, Canada, Mexico and Turkey). The cluster at the left comprises mostly Latin American and African currencies—although note the presence of Bangladesh and Brunei. The two small clusters at the bottom connect triads of currencies. The figure has been drawn using the Pajek software

as Turkey and Mexico from the "Next Eleven" (N-11) group identified in Ref. [28] as countries having the potential of becoming some of the largest economies in the world in the coming years—and a few non-European developed economies such as Australia and Canada. The even larger cluster comprising eleven currencies is dominated by the countries of Asia-Pacific such as Taiwan and Singapore as well as the N-11 countries Indonesia, Korea and Philippines, which have either developed or fast growing economies; however, through the Japanese Yen, these currencies are also connected to a smaller sub-cluster of European currencies which contains the Euro apart from the Swiss and Danish currencies (note also the presence of the currency of Morocco, a north African country but one that has strong economic ties with Europe). The largest cluster has seventeen densely inter-connected currencies which are geographically spread around the world, although half of them are from Latin America or the Caribbean. Possibly this cluster reflects a new wave of fast growing economies (e.g., it includes two N-11 countries, Bangladesh and Pakistan) whose development trajectory may affect the global economy in the future as profoundly as the rise of India and China has affected it in the past decades.

11.4 Conclusions

In this article we have analyzed the topological structure of interactions in the world currency market by using the spectral properties of the cross-correlation matrix of exchange rate fluctuations. We see that the eigenvalue distribution is similar to that seen in equities markets and consists of a bulk approximately matching the predictions of random matrix theory. In addition, there are several deviating eigenvalues which contain important information about groups of strongly interacting components. However, the composition of the leading eigenvector shows a remarkable distinction in that, unlike the relatively homogeneous nature of the eigenvector for cross-correlations in the equities market where all stocks contribute almost equally to the market or global mode, the different currencies can have widely differing contributions to the global mode for exchange rate cross-correlations. This possibly reflects the extent to which the fluctuations of a currency is in sync with the overall market movement and may also be used to measure the influence of a currency in the world economy. While, as is probably expected, the large components of this mode mostly belong to currencies of the developed economies of western Europe as well as the rapidly growing economies of the Asia-Pacific region, there are unexpectedly strong contributions from currencies outside this group—such as those of Botswana, Bangladesh and Kazakhstan. This indicates that these economies may be playing an important role in directing the collective dynamics of the international currency market that is not exclusively dependent on their intrinsic economic strength, but rather the position they occupy in the network of interactions among the currencies. This is confirmed by the reconstructed network of interactions among the currencies as a minimum spanning tree. This network shows a segregation between clusters dominated by developed or rapidly growing economies on the one hand, and relatively underdeveloped economies on the other. While these two parts can show dynamics relatively independent of each other, a few currencies—those of Morocco, Botswana and Bangladesh—act as a bridge between them. Thus the role of these currencies as vital connecting nodes of the world currency market possibly give them a much more important position than would be expected otherwise. We have also used an alternative graph representation technique to identify several groups of strongly interacting currencies. Some of the smaller clusters may be reflecting possible economic or other relations between the corresponding countries. However, the largest cluster comprises a densely interconnected set of currencies belonging to countries that are geographically spread apart. We speculate that these could well belong to the next wave of fast emerging economies that will drive the economic growth of the world in the future. This is significant from the point of view of applications, as such economies are potentially lucrative targets for foreign investment and are eagerly sought after by portfolio fund managers. Methods of identifying early the next fast growth economies assume critical importance in such a situation. Our analysis of cross-correlations of exchange rate fluctuations suggests that prominent clusters in the reconstructed networks of interactions in the world currency market may potentially provide us with such methods.

Acknowledgements We would like to thank R K Pan who helped in developing the software used for the analysis reported here and S Sridhar for stimulating discussions. Part of the work was supported by the Department of Atomic Energy, Government of India through the IMSc Complex Systems Project (XII Plan).

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