Currency Co-movement and Network Correlation Structure of Foreign Exchange Market.

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Abstract

We study the correlations of exchange rate volatility in the global foreign exchange (FX) market from 4 January 2000 through 30 June 2014 based on complex network graphs. Correlation matrices (CM) and the theoretical information flow method (Infomap) are employed to analyze the modular structure of the global foreign exchange network. The analysis demonstrates that there exist currency modules in the network, which is consistent with the geographical nature of currencies. The European and the East Asian currency modules in the FX network are most significant. We further introduce a measure of the impact of individual currency based on its partial correlations with other currencies. We further incorporate an impact elimination method to filter out the impact of core nodes and construct subnetworks after the removal of these core nodes. The result from our method reveals that (i) the US Dollar has prominent global influence on the FX market while the Euro has great impact on European currencies; (ii) the East Asian currency module is more stable than the European currency module. The high stability is a result of the strong co-movement of currencies in the region. The impact analysis method is further used to study the basket of currencies used by the Chinese government for its currency policy and the result is in good agreement with the consideration based on international trade.

Keywords: Exchange rate; Complex network; Currency Co-movement

1. Introduction

Many complex systems can be studied from the perspective of weighted networks that link different elements within the system (Mantegna et.al.,1995; Watts et.al.,1998; Callaway et.al.,2000; Dorogovtsev et.al.,2003; Schweitzer 2009; Kumar et.al.,2012). In these complex systems, each interacting element in general corresponds to a node of the constructed network. Examples include gene regulation networks, food webs, financial markets, etc. The nodes in these networks interact and have impact on each other. Take the gene regulation networks (Li.,2005) as an example. Each gene in a gene regulation network is represented by a corresponding node and a link between two nodes establishes a probabilistic dependence between them. A gene can regulate the expression of other genes and thus form a pathway within the network. When and to what extent a gene is regulated by other genes is the key to an understanding of life. In a broader sense, the gene regulation network belongs to a class of networks which are known as correlation-based networks. In this kind of networks, nodes interact and affect each other. In some cases, several nodes could mutually interact with each other that are affected by a common source. In other cases, a node can transfer information to other nodes and thus affect their behavior. What is more interesting is that most of these correlation-based networks are non-stationary, nonlinear and non-equilibrium. Furthermore, the impact of a node on other nodes would also change as

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time evolves. Among these, the global foreign exchange (FX) network is one of the most interesting correlation-based networks (Ausloos, 2006). The FX network consists of mutually interacting nodes, where each node taking the value of the exchange rate of the corresponding currency.

Since the exchange rates between two nodes are correlated and constantly changing, correlation-based network methods are needed to detect the correlation relations between elements within the FX network. We here develop a quantitative analysis which will offer an explanation of one of the most interesting aspects of empirical exchange rate behavior, i.e., the high degree of co-movement of currencies which is consistent with their geographical nature. The currency co-movement reveals the fact that the fluctuations of currencies in the same region are highly correlated. In the language of complex networks, a currency sector of the co-movement is equivalent to a module in the FX network. In this paper, we will identify modules in the FX network and further analyze the currency co-movement phenomenon. There exist methods to study correlation-based networks in the literature (see Plerou et al., 1999; Mantegna et al., 2000; Bonanno et al., 2003; Tumminello et al., 2007; Shen et al., 2009; Kullmann et al., 2002; Jiang et al., 2014; Preis et al., 2012). Minimal Spanning Tree (MST) and Planar axiomally Filtered Graphs (PMFG) (see Kruskal, 1956; Bollobas, 1979; Rammal et al., 1986; Mantegna, 1999; Tumminello et al., 2005; Mai et al., 2014) are some of these methods that have been used to analyze the structure and dynamics of financial markets. Correlation matrices (CM) and the MST graphs are constructed to analyze the FX market (see McDonald et al., 2005; Brida et al., 2009; Kwapien et al., 2009; Drozdz et al., 2009) and interesting results have been found. Researchers identify the hierarchical structure and clusters in the FX market by using statistical physics techniques (Vandewalle et al., 1998; Ravase et al., 2003; Mizuno et al., 2006; Naylar et al., 2007), and these clusters often match nicely with the geographical regions such as Europe and Asia (see Mizuno et al., 2006; Keskin et al., 2011). Gorski (2008) shown that it is a scale-free network with a power law exponent similar to many other complex systems. The centrality of the US Dollar is weakening while the role of Euro is becoming increasingly important. Due to the peculiar features of the global FX market, some useful information cannot be detected by the methods mentioned above. For example, the FX market has the unusual characteristics of the so-called ‘Currency peg’, which means that some nodes (e.g., Hong Kong Dollar) may peg to the same core node (e.g., US Dollar) and give an illusion that these nodes have much stronger impact on other nodes. On the other hand, there are nodes mutually ‘interact’ with each other that have affected by a common source. For instance, Canada and Australia have high similarities in their exports like fuel and minerals, etc. Fluctuations in fuel and mineral prices would affect the value of both currencies and thus could result in having mutual correlations between the two currencies. Simply discarding some nodes in the network still leave behind their impacts on other nodes and render incorrect results in subsequent analysis. Therefore, one would need to employ methods that could filter out these effects in order to study the hierarchical structure and dynamical behavior of the FX network. In this paper, we will employ an impact elimination method to study the FX network.

2. Materials and Methods

2.1 Currency correlation matrix.

For currency \(i (i = 1, 2, \ldots, n)\) at time \(t\), we define its return \(R^B_{i}(t, \tau)\) over time period \(\tau\) as:

\[
R^B_{i}(t, \tau) = \ln e^B_{i}(t + \tau) - \ln e^B_{i}(t)
\]  

(1)

where \(\ln e^B(t)\) is the exchange rate of the currency \(i\) at time \(t\), i.e., a value of currency \(i\) expressed in terms of a base currency B. The return thus indicates the magnitude of rise or fall during \(t\) and \(t + \tau\). For ease of comparison among different datasets, the return given above will be standardized as \(r^B_{i}(t, \tau) = [R^B_{i}(t, \tau) - (R^B_{i}(t, \tau))] / \sqrt{(R^B_{i}(t, \tau))^2 - (R^B_{i}(t, \tau))^2}\), where \(\langle X \rangle\) stands for the average of \(X\) during the trading period. We then obtain the cross-correlation matrix \(C^B\) of the FX market (based on the currency B), whose elements \(C^B_{ij}\) denote the correlation between currency \(i\) and currency \(j\):

\[
C^B_{ij} = \langle r^B_{i}(t, \tau)r^B_{j}(t, \tau) \rangle
\]  

(2)

It is clear that \(C^B\) is a symmetric matrix with \(C^B_{ij} = 1\), and \(-1 \leq C^B_{ij} \leq 1\). We can further define the distance
matrix $D^p$: $d_{ij}^p = \sqrt{(1 - C_{ij}^p)/2}$. It is also clear that a large value of $C_{ij}^p$ or small value of $d_{ij}^p$ reflect a high correlation between currency $i$ and currency $j$. In this paper, we choose Swiss Franc (CHF) as the base currency $B$, which keeps a relatively stable value in the sample time, and here $\tau$ is chosen to be 1 day.

One could now use matrices $C$ and $D$ to construct correlation networks for the global FX market. We use MST and PMFG to construct the global FX network based on the correlation matrices $C$ and $D$. These network analyses will give us useful information about the topological and hierarchical structure of the global FX market.

### 2.2 Impact elimination method.

To filter out the impact of a node on other nodes, Follow Shapira et.al.,(2009) and Kenett et.al.,(2010) we here define a partial correlation and construct a new currency correlation matrix. For a node $k$ in the FX network, its correlation with nodes $i$ and $j$ are respectively $C_{ik}$ and $C_{jk}$. One can define the correlation between $i$ and $j$ after filtering out the impact of the currency $k$ as

$$C_{ij}/k = \frac{c_{ij} - c_{ik}c_{jk}}{\sqrt{(1-c_{ik}^2)(1-c_{jk}^2)}}$$

(3) for $i; j \neq k$. The impact factor $I_k$ of node $k$ can then be defined to measure the influence of node $k$ on the global FX network:

$$I_k = \frac{1}{2n'(n' - 1)} \sum_{k \neq i,j} (c_{ij} - c_{ij/k})$$

(4)

Where $n'$ is the number of remaining nodes after one eliminates node $k$, i.e., $n = n - 1$.

For a system which has multi-layered network structures, one would need to eliminate the impact of several nodes in the corresponding network. To analyze such multi-layer structures, we perform the following elimination procedures.

1. Assume that currency $k'$ is the node that we want to remove from the network and denote the set of removed nodes to be $K$. For the removed node $k'$, $K = \{k'\}$. To remove node $k'$, we also need to eliminate its influence on other nodes in the network. This is done by computing $c_{ik}$ and $c_{jk}$. The new correlation between the currency $i$ and $j$ for the new network after removing $k'$ will be given by Eq. (3).

2. After removing the impacts of the set of nodes $K$ on the network system, recalculate the impact factors of each remaining $n'$ nodes. Denote the new impact factor of node $z$ as $I_{z,k}$, where $I_{z,k} = \frac{1}{2n'(n'-1)} \sum_{x \neq i,j}(c_{ij}/K - C_{ij}/x,K)$.

3. Assume that currency $k$ is the node we want to remove from the remaining $n$ nodes in the network system. We can now eliminate $k$ and its influence on the other nodes in a similar fashion. After eliminating the impact of currency $k$, the new correlation between the currency $i$ and $j$ is given by $C_{ij}/k''$, $K = \frac{c_{ij}/K - c_{ik''}c_{jk''}/K}{\sqrt{(1-c_{ik''}^2)(1-c_{jk''}^2)}}$, for $i,j \neq k''$. The set of removed nodes becomes $K = \{k'', K\}$ and the number of remaining nodes becomes $n'' = n' - 1$.

4. Repeat steps (1) - (3) for nodes which one wants to remove.

### 3. Results

#### 3.1 Network Structure.

In order to obtain a reasonably long sample period, we collect daily data of 52 major currencies from the global FX market, including also gold and silver. The daily data cover the time period from 4 January 2000 through 30 June 2014, and is obtained from the Pacific Exchange Rate Exchange Rate Service available online.
http://fx.sauder.ubc.ca/data.html). To denote the currencies, we adopt the ISO4217 standard by using three-letter codes(http://www.iso.org/iso/home/standards/currencycodes.htm). To eliminate artifacts and extreme data points that can misleadingly dominate the outcomes, all time series are preprocessed and no data points are more than 5 standard deviations from the mean. As a result, each currency has 3636 observations. Due to the high quality of data, only a few data points are discarded and 99.76% of the original data points are kept for analysis.

Fig. 1 and 2 are the MST and PMFG graphs of the global FX market respectively. Each node represents an individual currency, and a link represents the correlation between two nodes. In a weighted network, each node $i$ owns its degree $d_i$ (the number of links attached to it) and weight $w_i$ (the sum of weights of nodes linked to node $i$). For a complex network, one can use the node weight $DW_i = \frac{w_i}{\sum w_i}$ and degree $D_i = \frac{d_i}{3n-6}$ to measure its influence. One can easily observe that in the global FX network as shown in Fig. 1 and 2, there are nodes which emerge as core nodes and have greater impacts on other nodes within the network. These core nodes own a large portion of links in the network. Table 1 shows the top eight currencies ranked by their node weights and degrees in the PMFG of the global FX market. The sum of node weights $DW_i$ of the top eight currencies accounts for 40.72% and 43.04% in the MST and PMFG networks respectively, while the sum of node degrees $D_i$ of the top eight currencies accounts for 84.31% and 77.33% in MST and PMFG networks respectively.

The US Dollar (USD) and European Euros (EUR) have great influences on the entire market, since they own a large number of links in the FX network. According to the Triennial Central Bank Survey 2013 of Bank for International Settlements (BIS), the trading volumes of USD and EUR totaled more than 60%. Although USD's function as a reference currency has been weakening (for instance, EUR is also a currency of settlement for oil in some countries nowadays), it is still very influential in the FX market. We will further analyze the influence of the currencies which appear in Table 1 as well as other currencies in the FX network in the next section.

**Figure 1. MST graph of the global FX market.** The bigger the size of a node, the larger the degree it is associated with; the thicker the link, the stronger the correlation between the nodes.
Figure 2. PMFG graph of the global FX market. The bigger the size of a node, the larger the degree it is associated with; the thicker the link, the stronger the correlation between the nodes. The color of a node indicates the module that the currency belongs to.

Table 1. Top 8 currencies ranked by their network weights and degrees in the PMFG of the global FX market.

<table>
<thead>
<tr>
<th>Ranking</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>K</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HKD</td>
<td>10.38</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>USD</td>
<td>7.30</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CNY</td>
<td>4.67</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SGD</td>
<td>4.58</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MYR</td>
<td>4.55</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TWD</td>
<td>4.37</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DKK</td>
<td>3.98</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EUR</td>
<td>3.21</td>
<td></td>
<td></td>
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</tbody>
</table>

We next investigate the community structure of the FX market. Economic globalization and regional economic integration have become two important factors in world economic development. For example, the European Union (EU) is now the most successful regional economy in the world. Fig. 3 gives the CM of the sample currencies in the FX market in which the numbers on the axes refer to the currencies arranged by regions, namely 1-12 correspond to the European currencies, 16-33 correspond to the Asian currencies, and 42-52 correspond to the American currencies. On the left, the color value of a cell relates to the strength of correlation between the currencies and figure on the right is the corresponding three-color grayscale. We here use green, red and yellow squares to indicate the relevance of currencies within Europe, Asia and America respectively, and use the blue squares to indicate the correlation between the American and Asian currencies.

Figure 3. CM of the global FX market. The numbers on the axes refer to the currencies arranged by regions, i.e. 1-12 correspond to the European currencies, 16-33 correspond to the Asian currencies, and 42-52 correspond to the American currencies. On the left, the color value of a cell relates to the strength of correlation between the currencies and figure on
the right is the three-color grayscale.

One can now observe the geographical regional characteristics of the FX market from Fig. 3. For the FX market network, identifying its modular structure is crucial to understand its topology and growth mechanism. We here detect the modularity of PMFG by using the theoretical information flow method (Infomap). The Infomap method is an information theoretic approach that can reveal community structures in networks, which is based on random walks on a network to capture the information flow (Rosvall et al., 2008, 2009). One can simplify and highlight the regularities in the community structure. The reader is referred to Ref. (Rosvall, 2009) for detailed description of the method. Referring to Fig. 2, we use different colors for the nodes to represent the different modules that the currencies belong to. There are 4 modules in PMFG, which we denote A, B, C and D. Table 2 shows the currencies in modules A, B and C. All currencies in Module A are European currencies. There are 13 European currencies in the dataset. Other than Turkish Lira (TRY) and Russian Ruble (RUB), they all belong to Module A. To reduce exchange rate variability and achieve monetary stability in Europe, EU implements the ERM II, thus most of the European currencies fluctuate with EUR (Parikh et al., 1996; Laopodis, 2013). Owing to the high economic integration, the currencies in this region are highly correlated. Although Russia belongs to Europe geographically, Russia is still free from European treaties, due to historical reasons. One also notices that although Turkey's territory extends from Europe to Asia, it is not a member of EU. These facts could therefore explain why we do not find RUB and TRY in Module A. Except for Colombian Peso (COP) and RUB, all currencies in Module B are (East) Asian currencies. Although East Asia does not have an economic community as EU, most East Asian economies hope to form a tight connection via the long-term mutual cooperation and integration process. In fact, many multiple institutional frameworks already exist, such as the ASEAN+3, the Asia-Pacific Economic Cooperation Organization and the Regional Comprehensive Economic Partnership. In Module C, most of the currencies belong to countries in Oceania (e.g. AUD, NZD) and Latin America. The remaining 21 currencies belong to Module D, and no obvious regional characteristics could be found.

### Table 2. The modularity of the FX market.

<table>
<thead>
<tr>
<th>Module</th>
<th>ModuleA</th>
<th>ModuleB</th>
<th>ModuleC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rankings</td>
<td>$k$</td>
<td>$DW(%)$</td>
<td>$D(%)$</td>
</tr>
<tr>
<td>1</td>
<td>DKK</td>
<td>3.11</td>
<td>6.67</td>
</tr>
<tr>
<td>2</td>
<td>EUR</td>
<td>2.87</td>
<td>6.00</td>
</tr>
<tr>
<td>3</td>
<td>GBP</td>
<td>1.98</td>
<td>4.67</td>
</tr>
<tr>
<td>4</td>
<td>BGN</td>
<td>1.78</td>
<td>4.67</td>
</tr>
<tr>
<td>5</td>
<td>HUF</td>
<td>1.62</td>
<td>3.33</td>
</tr>
<tr>
<td>6</td>
<td>SEK</td>
<td>1.36</td>
<td>2.67</td>
</tr>
<tr>
<td>7</td>
<td>CZK</td>
<td>1.35</td>
<td>2.67</td>
</tr>
<tr>
<td>8</td>
<td>NOK</td>
<td>1.27</td>
<td>2.67</td>
</tr>
<tr>
<td>9</td>
<td>PLN</td>
<td>0.99</td>
<td>2.00</td>
</tr>
<tr>
<td>10</td>
<td>RON</td>
<td>0.84</td>
<td>2.00</td>
</tr>
<tr>
<td>11</td>
<td>ISK</td>
<td>0.54</td>
<td>2.00</td>
</tr>
</tbody>
</table>

### 3.2 Measuring currency influence on the network.

The above result indicates that currencies like Hong Kong Dollar (HKD), Chinese Yuan (CNY), Singapore Dollar (SGD), Malaysian Ringgit (MYR), Taiwanese Dollar (TWD) and Danish Krone (DKK) have large impacts on others, and interesting enough HKD appears even more influential than USD. From the cross-correlation matrix C, we find that the exchange rate fluctuations of these currencies are highly correlated with either USD or EUR, since these currencies are pegged to USD (DKK is pegged to EUR) to some degree. For instance, Hong Kong has implemented the Linked Exchange Rate System since 15 October 1983, i.e. HKD is pegged to USD and keeps the exchange rate at 1 USD 7.8
HKD. The correlation coefficient of exchange rate fluctuations between USD and HKD is 0.9997, which results in the high degree value of the HKD in MST and PMFG. Similarly, the correlation coefficient of USD/SGD, USD/MYR, USD/CNY and USD/TWD are respectively 0.834, 0.863, 0.988 and 0.895. In an analogous way, the large influence of DKK in the FX market shown by MST and PMFG is related the fact that DKK is pegged to EUR. Denmark has not joined the euro zone, following a rejection by referendum in 2000. In order to resist the adverse effects of volatile exchange rates, DKK is pegged closely to EUR via the EU’s exchange rate mechanism (ERM II), and keeps the exchange rate to be within the narrow range of ±2.25% against the central rate of 1 EUR = 7.460 DKK. As a result of the currency peg mechanism in the FX market, network graphs like MST and PMFG could not effectively reflect the genuine impact of a node on other nodes in the FX network. This means if one wants to study the hierarchical structure of the FX network, it is necessary to filter out the impact of core nodes in the network graphs in order to study the corresponding substructures. We now analyze the hierarchical structure of the currency network by removing nodes and filtering out their influences on others in the FX network. Since there are currency pegs to the USD and EUR, one would want to remove them in order to see the topological and hierarchical structure of the sub-networks which consist of other currencies. We remove USD and EUR from the currency system by using the impact elimination method and obtain new rankings of currencies in the FX market in the new currency subnetwork (without USD and EUR). The 8 highest ranking currencies of this new network in order are AUD, SGD, Mexican Peso (MXN), Polish Zloty (PLN), Canadian Dollar (CAD), New Zealand Dollar (NZD), MYR and Hungarian Forint (HUF).

3.3 Network structure of the FX market from impact analysis.

We here study the topological and hierarchical structure of the FX market from the impact analysis of currencies. The analysis above indicates that USD and EUR have great impacts on many other currencies. A related question is whether the currency modular structure still exists after we remove these two core nodes and filter out their impacts from the FX network. As a matter of fact, most East Asian economies implemented a highly dollar-peg exchange rate mechanism for a long term in history. In particular, after the 1997 Asian Financial Crisis, East Asia formed a dollar-centric "dollar zone" over a long period of time (Stiglitz, 2001). One would want to ask how this pegging mechanism could possibly affect the East Asian currency exchange rate linkage within the network. We therefore remove the USD and EUR from the FX network and study the topological and hierarchical structures of the corresponding subnetworks. In Fig. 4, the two graphs represent the currency correlation network graphs after filtering out the influence of USD and EUR respectively, and the different colors of nodes indicate that they belong to different modules. Fig. 4(a) is the PMFG network graph after the removal of USD. Compared to the network in Fig. 2, the modular binding appears weaker. The entire FX market now partitions into six modules but the East Asian currency and European currency modules still exist. Fig. 4(a) also shows that after filtering out the impact of USD, the influences of DKK, EUR, HUF and other European currencies appear to become more prominent, while the influence rankings of HKD, CNY and TWD drop dramatically, meaning that the great influences of these currencies owe much to the fact that they are pegged to USD. Similarly, after removing EUR from the FX market in Fig. 4(b), the influence rankings of many European currencies decline sharply. These European currencies could not form a currency module anymore but in fact distribute into different modules while the East Asian currency module still exists. Finally, after removing the impacts of both USD and EUR in Fig. 4(a), the influence rankings in the currency network change significantly, and the AUD and MXN appear to be the most influential. In this case, the regional characteristics of the modular structure in the FX market becomes unclear. The European currency module disappears while the East Asia currency module could still be identified. Fig. 6 shows the CM graphs after we filter out the influence of both USD and EUR. After filtering out the impact of USD (left figure), European currencies still maintain a high correlation but the CM elements of other currencies reduce dramatically, meaning that USD has a great effect on most of currencies except the European currencies. On the other hand, after filtering out the impact of EUR (right figure), the correlations of exchange rate volatility between European
currencies weaken significantly, which suggests that the European currency linkage is ascribed to their high correlations with EUR. The impact analysis demonstrates the prominent global influence of USD and the impact of EUR on European currencies. The European currency module disappears when one removes the impact of EUR from the FX market. Another interesting point is that the East Asia currency module appears to be more stable than the Europe currency module, which could be observed from Fig.4 and 5. Although the cross correlations between Asian currencies decline sharply after we remove USD from the network, one can still observe the formation of East Asian currency module. Government policies and the frequent contacts among economies may be the factors for the stability of the East Asian currency module.

![Figure 4. Currency correlation networks after removing the USD and EUR.](image)
(a) and (b) depict respectively the PMFG network graphs after eliminating the influence of USD and EUR.

![Figure 5. Currency correlation network after removing both USD and EUR.](image)

It is known that most emerging economies in Asia adopt an export-oriented economic growth model. In order to maintain the relative export advantage, their exchange rate systems have abandoned the originally recessive ‘dollar alliance’ but instead begin to price with the reference of a basket of currencies. To keep a competitive advantage in export markets, an economy needs to maintain focus on other economies in the region and to regard their currency exchange rates as an important reference to manage its local currency. In addition to policy approaches, East Asian economies have frequent contacts through trades and capital flows, which lead to the high correlations of their currencies. Therefore, even without the impact of USD, similar policies of referencing the currency basket and the high trade contacts among the regional economies result in a stable East Asian currency module structure. This results in a strong co-movement of currencies within the region. Another interesting issue that could be studied by using the elimination method is to identify the basket of currencies that are being used by countries like China. In 2005, the Chinese government announced that its currency would fluctuate with respect to a basket of foreign currencies. In the initial stage, the government chose a basket of currencies, including USD, HKD, EUR, British Pound (GBP), AUD, CAD, SGD, MYR, Japanese Yen (JPY),
Korean Won (KRW) and RUB. The consideration is mainly based on international trade. One can ask if these currencies indeed have high influence on other currencies in the FX network. Our strategy is to study the impact ranking of the FX network. We again rank the impact of each currency according to Eq. (4). The top 10 impact ranking currencies are listed in in Table 3, Column I. Most of the listed currencies have very high correlations with the USD. Therefore, their genuine impact is obstructed by their correlations with the USD. To uncover their genuine impact on other currencies, we use Eq. (3) to filter out the impact of USD from the FX network and construct a new weighted network without the USD node. The new top 10 impact ranking currencies are listed in Column II. One can now see that several of the high ranking currencies in Column I drop out of the list in Column II. Many of the European currencies appear in this new list and most of them are highly correlated with EUR. In order to see their genuine impact on other currencies, we again filter out the impact of EUR by using Eq. (3) and obtain a new list in Column III. We now see that many of the currencies appear in Column III are in the basket of reference currencies. The ones that do not appear in the list include, e.g. KRW and RUB, which would be the 11th and 14th node to be removed if we continue the elimination process. HKD is pegged to USD and GBP is highly correlated with EUR and their impacts on other currencies are mainly through USD and EUR. Their influences on other currencies drop tremendously after we remove the USD and EUR from the FX network. As a side note, we can remove HKD first since it is a tiny fraction higher than USD in the original impact factor list. In this case, if we continue the elimination process, USD will be about the 10th node to be removed. However, if we eliminate USD first, the impact ranking of HKD will immediately drop to below 30. This is strong evidence that USD should be treated as a core node instead of HKD. Another interesting observation is that in the beginning, CAD is among the top 10 most influential currencies. Its impact is more evident after removing both USD and EUR. However, its impact drops dramatically after we remove the AUD node. The reason is probably due to the fact that Australia and Canada have high similarities in their exports and thus are mutually correlating with each other through this common background. It is interesting to see that the basket of currencies from both the consideration of international trade and from our analysis of their impact in the global FX network are in agreement with each other except for JPY. JPY does not appear to have much impact on other currencies in the FX network but is still the third most traded currency in the market.

Table 3. Top 10 impact ranking currencies from the elimination process.

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<thead>
<tr>
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<td>2</td>
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<tr>
<td>3</td>
<td>SGD</td>
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<td>MXN</td>
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<td>EUR</td>
<td>PLN</td>
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<td>DKK</td>
<td>CAD</td>
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<td>6</td>
<td>TWD</td>
<td>NOK</td>
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</tr>
<tr>
<td>7</td>
<td>HNL</td>
<td>SEK</td>
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</table>
4. Conclusion

In this paper, we used complex network graphs to analyze the correlations of exchange rate volatility in the global FX market. We identified core currencies, namely USD and EUR that have great impacts on the exchange rate fluctuations of other currencies. To investigate the currency co-movement behavior in the FX market, we utilized CM analysis and the theoretical information flow method (Infomap) to investigate the modular structure of the currency network and found several modules in the FX market. This modular structure is in agreement with the geographical nature of currencies where the European currency module and the East Asian currency module are most significant.

Due to the presence of the currency peg mechanism in the FX market, network graphs like MST and PMFG could not effectively reflect the genuine influence of a node on other nodes in the FX network. To analyze the hierarchical structure of the FX network, we introduced an impact elimination method to filter out the impact of a currency when it is being removed from the network.

Based on this method, we investigated the topological and hierarchical structures of the subnetworks of other currencies by removing core nodes like USD and EUR and uncovered several interesting phenomena. Results from the elimination method show that international currencies, e.g. USD and EUR have high impacts on the FX network, in particular the prominence of global influence of USD and the great impact of EUR on European currencies. Another interesting phenomenon is that the East Asian currency module appears to be more stable than the Europe currency module since the former can still be observed after the removal of these core currencies whereas the European currency module will disappear as one filters out the impact of EUR on the FX market.

This is probably related to the regional trade and the currency policies coordination between the countries in the region. The highly stable East Asian module is indeed a result of the strong co-movement of currencies in the region. As a further application, we also measured the impact of currencies that appear in the basket of currencies used by the Chinese government and found that the basket of currencies from both the consideration of international trade and their impact in the global FX network are in agreement with each other. The methods employed in this paper are useful tools for analyzing other real world complex correlated systems.

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References


