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*Research Article*

# Analysis of Linkage Effects among Currency Networks Using REER Data

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We modeled the currency networks through the use of REER (real effective exchange rate) instead of a bilateral exchange rate in order to overcome the confusion in selecting base currencies. Based on the MST (minimum spanning tree) approach and the rolling-window method, we constructed time-varying and correlation-based networks with which we investigate the linkage effects among different currencies. In particular, and as the source of empirical data, we chose the monthly REER data for a set of 61 major currencies during the period from 1994 to 2014. The study demonstrated that obvious linkage effects existed among currency networks and the euro (EUR) was confirmed as the predominant world currency. Additionally, we used the rolling-window method to investigate the stability of linkage effects, doing so by calculating the mean correlations and mean distances as well as the normalized tree length and degrees of those currencies. The results showed that financial crises during the study period had a great effect on the currency network's topology structure and led to more clustered currency networks. Our results suggested that it is more appropriate to estimate the linkage effects among currency networks through the use of REER data.

## 1. Introduction

The application of complex network analysis to financial data has attracted considerable interest in recent years [1–4]. Particularly, many scholars have focused their studies on the currency networks by using network-based correlation approaches, given that the foreign-exchange market, as the largest, most influential financial market, could directly or indirectly affect all other financial markets [5–10]. Most studies have employed the physics-derived method—namely, the minimum spanning tree (MST), which is robust but simple—to investigate the topological structure and statistical features of financial markets [11, 12]. Nevertheless, the MST results in the aforementioned investigations differ significantly, one reason being that the way to build correlation coefficient matrices varies to a great extent. Some scholars choose the Pearson correlation coefficient (PCC), which reflects the linear correlation between two stable time series, to build correlation coefficient matrices [13–15]. However, the financial time series usually demonstrate the nonlinear and nonstationary characteristics in real life, for example, the "stylized fact" of fat-tailed distribution in the return series [16]. Hence, other methods (e.g., the time-varying copula approach [10], phase synchronous information approach [9], etc.) to compute correlation coefficients among currencies have been used instead.

The aforementioned research has mainly focused on the use of a novel method to describe the interdependencies among different currencies, but few studies have focused on the confusion that occurs in the selection of base currencies, which is vital to the construction of correlation coefficient matrices. In the relevant literature it is a general problem to choose a numeraire, due to the fact that all currencies are mutually priced, thereby resulting in the absence of an independent numeraire [17]. For example, Mizuno et al. suggested the use of precious metals such as the gold, silver, and platinum, as the numeraire [18]. Nevertheless, other scholars have insisted that precious metals are inappropriate choices due to their high volatilities. Various numeraires besides the precious metals have also been used, such as the dollar, the minor currency, and the SDR [5–7]. Kwapień et al. [8] analyzed the data sets of daily foreign-exchange rates for 63 currencies and observed that there was no absolute correlation structure among the foreign-exchange networks. Instead, they found that its structure was largely dependent on the choice of base currency and the associated reference frame. In other words, the temporal evolution of the global currency system expressed by relevant exchange rates is actually the evolution of the frame in which the base currency rests. To express it simply, the use of bilateral exchange rates to construct foreign-exchange networks may obtain multifarious results because of the different choice of numeraire.

Thus the real effective exchange rate (REER) is considered to be a more important, authentic indicator, as it is able to reflect the real purchasing-power levels for currencies [19, 20]. Moreover, the REER data is calculated as weighted averages of bilateral exchange rates. Hence, there is no need to select a numeraire so all the currencies in our sample can be employed. Additionally, the current research mainly focuses on the topological structure and statistical features, but few studies have been associated with the inherent meaning of the economic phenomena. We therefore aim to use REER to substitute for the bilateral exchange rate and propose a network approach by combining the rolling-window method and the MST method as the means to investigate the topological and statistical natures of currency networks.

This methodology has been applied in two procedures, as follows. First, we collected 61 major currencies' monthly REER data over the period of 1995 to 2014, in which the world witnessed the Asian crisis of 1997 and the U.S. subprime credit crisis of 2007. The variety of bilateral exchange rates, being reliant on the choice of the base currency as the numeraire leading to the diversification of currency networks, depends entirely on the researchers' preference. In other words, the selection of a numeraire has no credible scientific foundation. To elaborate, the REER we employed was the average exchange rate of a basket of the foreign trade-weighted currencies adjusted for inflation. It could serve as a reasonable reference value for our research of the structure, topology, and nature of currency networks. Secondly, we used rolling-window methods to construct the dynamic cross-correlation matrices (CMs) of the 61 major currencies [21–24]. We then transformed the CMs into currency networks through the filter method of the MST in order to analyze the linkage effects of currency networks. Correlations in rolling windows were calculated in order to explore the dynamics of linkage effects. From a methodological perspective, these are the main contributions of this paper.

The rest of the paper is organized as follows: Sections 2 and 3 represent the empirical data and methodological issues. We construct currency networks in different window lengths and then present the main empirical results and analyses in Section 4. We then draw conclusions in Section 5.

## 2. Data

We studied the REER for a set of 61 major currencies from January 1994 to November 2014. The data set we selected included the monthly index offered by the Bank for International Settlements (BIS). An effective exchange rate (EER) offered a better indicator of the financial effects of exchange rates than any single bilateral rate could. A nominal effective exchange rate (NEER) is an index of the weighted averages of bilateral exchange rates. A real effective exchange rate (REER) is the NEER deflated by relative consumer prices. EERs serve various purposes: as a measure of international competitiveness, as components of monetary/financial conditions indices, as gauges of the transmission of external shocks, as intermediate targets for monetary policy, or as an operational target. Because the REER data was calculated as weighted averages of bilateral exchange rates, it was not necessary to select a numeraire and all the currencies in the sample could be used. Moreover, it should be mentioned that the sample in this study is fully consistent with the official data provided by the BIS, thus being more credible and truthful. The 61 currencies in our research and the respective currency symbols are presented in Table 1.

Financial crises have occurred periodically since the 1990s. In order to further investigate the changes of the linkage effect among different currencies under the impacts of financial crises, we selected the sample including the Asian crisis and the U.S. subprime crisis, whereupon we compared the results of static MST and dynamic rolling window.

## 3. Methodology

*3.1. Minimum Spanning Tree.* This paper uses Kruskal's algorithm to construct a minimum spanning tree (MST) as a means to show the linkage effects among different currencies. A brief description of how to construct a MST is as provided by Mantegna [25]:

> Step 1: Consider each currency as node and linkage effect as an edge in a network. Regard each node as an isolated branch and sequence the edges by their weights, which represent the degree of linkage effects among currencies.
>
> Step 2: Pass through the network once and search an edge that has the minimum weight. That is to say, such an edge represents the strongest linkage effect. Be sure the edge does not form a closed loop with those that have already been added to the minimum spanning tree. If all the requirements are met, this edge is added to the minimum spanning tree set. Otherwise, continue to pass through the network to find a different edge that has the minimum weight.
>
> Step 3: Recursively repeat the former steps until $n - 1$ edges have been searched. (If the network has $n$ nodes, the minimum spanning tree should have $n - 1$ edges because there are no closed loops in MST.) The search process is thus terminated and the network's minimum spanning tree is constructed. The MST connects the $N$ currencies (nodes) with $N - 1$ stronger links so that no loops are produced; that is, the MST of the currency network is represented with the strongest linkage effects of each currency.

Table 1: Sixty-one currencies and their symbols.

| Country | Currency | Country | Currency | Country | Currency |
|---|---|---|---|---|---|
| Algeria | DZD | Greece* | GRD | Peru | PEI |
| Argentina | ARS | Hong Kong* | HKD | Philippines | PHP |
| Australia* | AUD | Hungary | HUF | Poland | PLZ |
| Austria* | ATS | Iceland | ISK | Portugal* | PTE |
| Belgium* | BEF | India | INR | Romania | ROL |
| Brazil | BRZ | Indonesia | IDR | Russia | RUR |
| Bulgaria | BGL | Ireland* | IEP | Saudi Arabia | SAR |
| Canada* | CAD | Israel | ILS | Singapore* | SGD |
| Chile | CLP | Italy* | ITL | Slovakia | SKK |
| China | CNY | Japan* | JPY | Slovenia | SIT |
| Chinese Taipei* | NTD | Korea* | KRW | South Africa | ZAR |
| Colombia | COP | Latvia | LVL | Spain* | ESP |
| Croatia | HRK | Lithuania | LTL | Sweden* | SEK |
| Cyprus | CYP | Luxembourg | LUF | Switzerland* | CHF |
| Czech | CSK | Malaysia | MYR | Thailand | THB |
| Denmark* | DKK | Malta | MTL | Turkey | TRL |
| Estonia | EEK | Mexico* | MXP | United Arab Emirates | DHS |
| Finland* | FIM | Netherlands* | NLG | United Kingdom* | GBP |
| France* | FRF | New Zealand* | NZD | United States* | USD |
| Germany* | DEM | Norway* | NOK | Venezuela | VEB |

Note: countries marked with ∗ come from the BIS narrow indices.

*3.2. Calculation Method.* We use the REER data released by BIS [19, 20], which is calculated as

$$\text{REER}_t = \prod_{i=1}^{N} \left( \frac{e(i)_t}{\inf(i)_t} \right)^{w(i)} \cdot \inf_t, \tag{1}$$

where $\text{REER}_t$ is the real effective exchange rate of the country under study against a basket of currencies of trading partners, $\inf_t$ is the consumer price index of the country under study, $e(i)_t$ is the nominal bilateral exchange rate between the country under study and its trading partner $i$ at time $t$ (measured as the foreign-currency price of one unit of domestic currency), $w(i)$ is the weight of trading partner $i$, and $N$ is the number of trading partners considered, $\sum_{i=1}^{N} w(i) = 1$. The weights are derived from manufacturing trade flows and capture both direct bilateral trade and third-market competition by double-weighting. BIS uses geometrically weighted averaging because it is the most frequently used method in the literature. We use logarithmic yields to calculate correlation coefficients and distances among currencies. We define the return of currency $i$ on month $t$, as follows:

$$r_i(t) = \ln P_i(t) - \ln P_i(t-1), \tag{2}$$

where $P_i(t)$ denotes the monthly REER of currency $i$ on month $t$. Therefore, the correlation coefficient between indexes $i$ and $j$ is defined as

$$\rho^t_{ij} = \frac{\langle r_i^t r_j^t \rangle - \langle r_i^t \rangle \langle r_j^t \rangle}{\sqrt{\left[ \langle r_i^{t2} \rangle - \langle r_i^t \rangle^2 \right] \left[ \langle r_j^{t2} \rangle - \langle r_j^t \rangle^2 \right]}}, \tag{3}$$

where $\langle \rangle$ shows a time average over the trading days included in the return vectors. We transform the correlation coefficients to distance between two indexes, defined as

$$d^t_{ij} = \sqrt{2\left(1 - \rho^t_{ij}\right)}. \tag{4}$$

The function fulfills the requirements of distance. The distance matrix is used to determine the minimum spanning tree (MST) of the distances. The MST method in this paper is based on the work of Mantegna [25]. The MST for 61 currencies is constructed using Kruskal's algorithm and is presented in Section 3.1.

Additionally, we calculate the topological and statistical properties of currency networks. We investigate the mean of correlation coefficients as well as the mean of distances in order to study the dynamic linkage effects of currency networks. The mean correlation coefficients are as follows:

$$\overline{\rho} = \frac{1}{N(N-1)} \sum_{i \neq j} \rho^t_{ij} = \frac{2}{N(N-1)} \sum_{i<j} \rho^t_{ij}. \tag{5}$$

The mean of distances in the distance matrix is as follows:

$$\overline{d} = \frac{1}{N(N-1)} \sum_{i \neq j} d^t_{ij} = \frac{2}{N(N-1)} \sum_{i<j} d^t_{ij}. \tag{6}$$

The normalized tree length (NTL) is proposed [26, 27], being used to analyze the linkage effects among different currencies.

It is defined by

$$\mathrm{NLT}(t) = \frac{1}{N-1}\sum_{d_{ij}\in D} d^{t}{}_{ij}, \quad (7)$$

where $D$ is the set of edges in MST.

Yang et al. [28] suggested a measure called the maximum number of links, which is denoted as the number of links of the most connected currency in the MST. The more links a currency has, the greater linkage effect it exerts on other currencies.

## 4. Results

*4.1. Overall Pictures.* In order to explore the overall picture of interdependence relationships and linkage effects among the analyzed currencies, the following calculations were made. Distance matrices were calculated in rolling windows of 12 months in order to calculate the normalized tree length, mean distance, mean correlation coefficient, and maximum number of links. The normalized tree length and mean distance comprise the mean of the distances in the MST and distance matrices. The lower the value of the normalized tree length and mean distance is, the tighter the linkages among the currencies will be. Similarly, the mean of all the correlation coefficients gives us an idea of the interdependence among all currencies. Contrastingly, a higher value in the mean of correlation coefficients infers a tighter coupling among the countries.

Figures 1 and 2 present the normalized tree length (7) and mean distance (6) among all currencies in the foreign-exchange market from 1995 to 2014. The time window for both is $T = 12$ months (one year).

A very straightforward observation is that the mean distance fluctuated in a manner similar to the normalized tree length. The normalized tree length and mean distance both decreased around the time of the Asian crisis and the U.S. subprime crisis. Particularly, the NLT dropped dramatically around those crises and rebounded smoothly in the aftermath. The normalized tree length periodically floated up and down around the range of 0.55 to 0.75, and the mean distance fluctuated between 1.3 and 1.4. In the case of the Asian crisis, the normalized tree length and mean distance jumped abruptly at the beginning and then slowly decreased. After the Asian crisis, the Russian ruble crashed in 1998. We can observe a similar pattern between 1998 and 2000, in which the normalized tree length and mean distance periodically floated up and down. In the case of the U.S. subprime crisis, the normalized tree length and mean distance dropped to even lower levels as compared to the Asian crisis, meaning that the linkage effects among currencies became stronger. Between the two crises, the normalized tree length and mean distance increased gradually. During that time, the Russian default, Brazilian devaluation, and Argentine crisis occurred. Because those crises were somewhat regional and limited to a few nations, their effects on the currency networks were relatively small. It is not difficult to see that the normalized tree length and mean distance can catch the periodicity of a financial crisis. Our results are consistent with the findings cited [5].

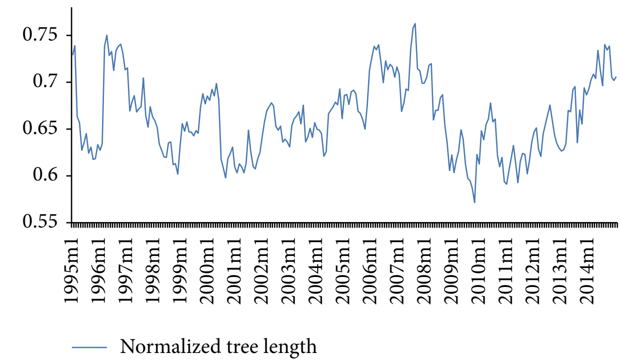


FIGURE 1: Normalized tree length as a function of $T$. We used time windows of $T = 12$ months and window step length parameter $\Delta T = 1$ month.

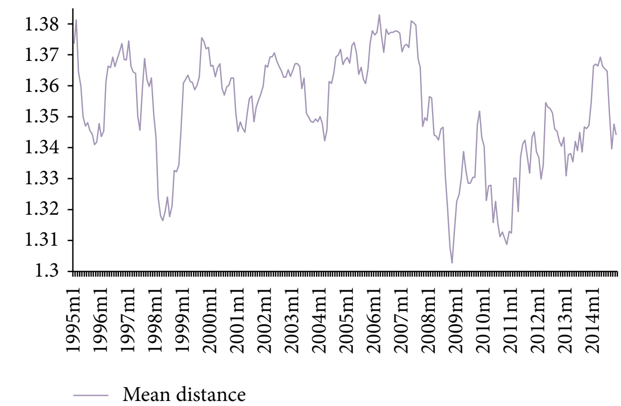


FIGURE 2: Mean distance as a function of $T$. We used time windows of $T = 12$ months and window step length parameter $\Delta T = 1$ month.

Figure 3 presents the mean correlation coefficient between all currencies in the foreign-exchange market from 1995 to 2014. The time window for the mean distance is $T = 12$ months (one year).

The mean correlation coefficient periodically floated up and down and increased around the time of the Asian crisis and the U.S. subprime crisis. In the case of the Asian crisis, the mean correlation coefficient jumped abruptly and dropped for the period. In the case of the U.S. subprime crisis, the mean correlation coefficient increased to an even higher level as compared to the Asian crisis, meaning that the linkage effects among currencies became stronger. Between the two crises, the mean correlation coefficient was stably maintained at a very low level. During that time, the Russian default, Brazilian devaluation, and Argentine crisis occurred. Because those crises were somewhat regional and limited to a few nations, their effects on the currency networks were relatively small. It is not difficult to see that the mean correlation coefficient can catch the periodicity of a financial crisis.

Figure 4 presents the variation tendency of the maximum number of links in the samples which range from 4 to 7. It is observed that the maximum number of links increased

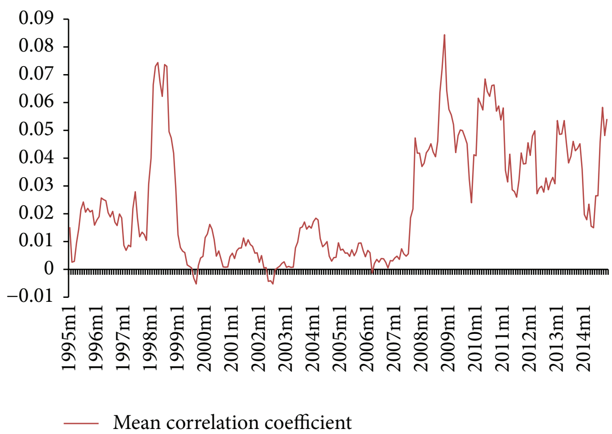


Figure 3: Correlation coefficient as a function of $T$. We used time windows of $T = 12$ months and window step length parameter $\Delta T = 1$ month.

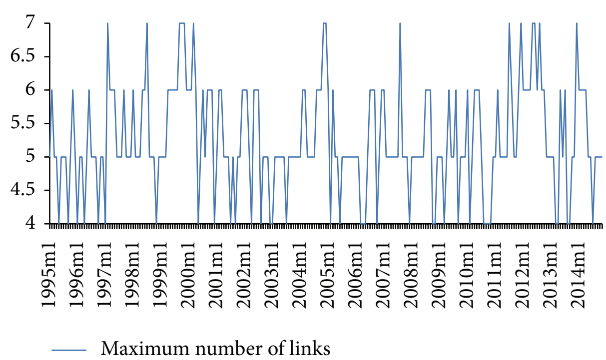


Figure 4: Maximum number of links as a function of $T$. We used time windows of $T = 12$ months and window step length parameter $\Delta T = 1$ month.

obviously during two time intervals, namely, 1997–2000 and 2011–2013, indicating an enhancing linkage effect during financial crises.

*4.2. Minimum Spanning Tree Analysis.* The MSTs have been directly constructed from the distances' matrices (3), from $\rho^{t}{}_{ij}$. This is a straightforward construction, as explained in Mantegna [25].

Three groups of countries are clearly seen in Figure 5, which presents the MST of the overall samples. The group of EU countries appears in first place with the smallest distances between them; next follow the energy exporting and importing countries; and in third place are the Southeast Asian countries. Interestingly, the USD is not the most linked currency in the network, even though it is the predominant world currency. This suggests that it might be better for countries to form a monetary union in order to obtain stability with commercial partners. However, strong linkage effects in the European countries are due to the common exchange rate policy of the European Monetary System before 1998 and the transition to a common currency, that is, the euro, in January 1999. The European cluster with EUR at its center is comprised of most currencies from the euro zone. The FIM, FRF, ATS, ESP, PTE, DEM, NLG, and IEP are directly linked to the EUR, while the SIT, MLT, PTE, BEF, EEK, LUF, CYP, GRD, and ITL are indirectly linked to the EUR. In brief, there is an outstanding linkage effect of the euro zone. Moreover, the energy cluster with SAR at its center is comprised of most currencies from major energy-trading nations such as USD, CNY, DHS, and DZD. These countries are endowed with more weight by trade-weighted REER on account of the large proportion of energy trade in the worldwide bilateral trade, leading to a strong linkage effect among their currencies. Likewise, East Asia demonstrates a strong linkage effect due to its geographical position and frequent commercial communication. The findings of clustering shown in the euro zone and East Asia conform to the earlier literature [8, 9]. It is noteworthy that the USD is always located at the center of clusters linked to currencies with various geographical distributions in a majority of the literature, where the USD cluster is called an international cluster [10]. In order to illustrate the robustness of the results related to the USD, we plotted the variation tendency of links of the USD, EUR, and CNY at different time windows (Figures 8 to 11). The degree to which the euro maintains an overwhelming advantage shows that, from the dynamic perspective, the euro zone has a strong linkage effect while the other important currencies like the USD and CNY are not always located at the center of the cluster. This is assertive evidence for the robustness of the results based on REER compared to that based on a bilateral exchange rate, although the robustness may, to some extent, diminish certain linkage effects.

Several features can be seen in Figure 6, which represents the structure information for 61 countries during the Asian financial crisis: There is a significant increment on the linkage effects of currencies in Asia, which is reflected in the reduced mean distance shown in the rolling window based on a time period of 12 months. Compared to the monetary cluster with THB at the center in Figure 5, whose distances with the linked currencies are 0.92, 0.94, 0.96, and 1.08, respectively, apparent changes occurred in the international FX markets around the years of the Asian financial crisis. In Figure 6, an obvious monetary cluster is observed with PHP at the center, whose distances with the linked currencies are 0.42, 0.54, and 0.43, respectively. In other words, countries connect more tightly while the comovements among them are more intense in the FX market. This is reflected in the decreasing average path length of the MST, which suggests that the Asian financial crisis would contribute to the increase of linkage effects among the East Asian currencies. One conflicting observation is noteworthy in the fact that the degree of THB in Figure 5 is greater than that of PHP in Figure 6, which suggests that the financial crisis may not strengthen the linkage between currencies. However, this finding may be biased due to the reason that there are other regions indirectly linked to PHP. To further dig into the nature of linkage effect around the time of the Asian financial crisis, we plotted the sum of degrees of ten East Asian currencies (the CNY, HKD, NTD, JPY, KRW, MYR, PHP, THB, INR, and

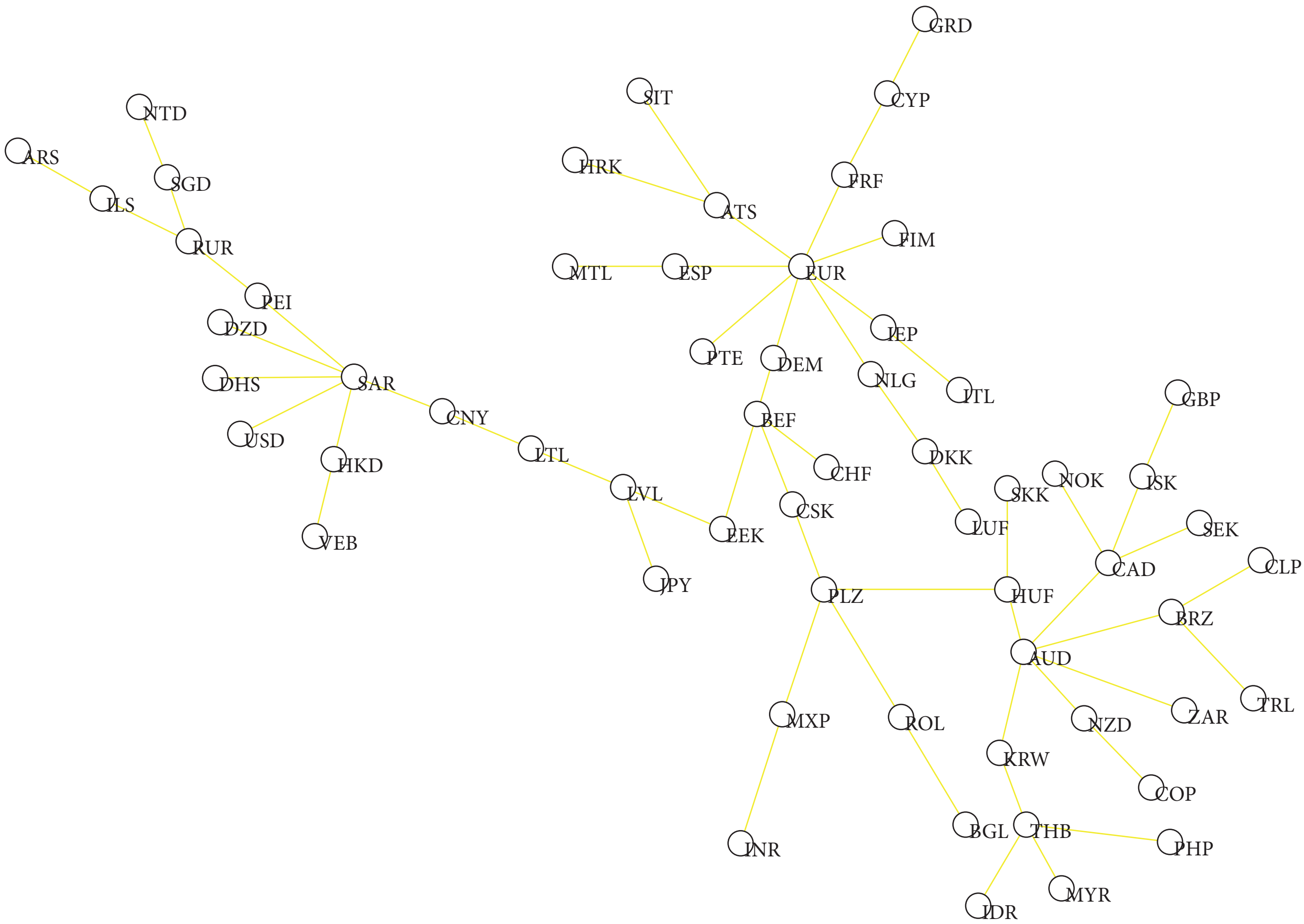


Figure 5: MST of 61 currencies during February 1994–November 2014, as an overall picture.

SGD) during the Asian crisis of 1997. The result is presented in Figure 12. As one can see, during that time interval the sum of degrees regarding the above-mentioned ten regions reaches an unprecedented level (above 25), providing strong proof that the Asian financial crisis led to the general enhancement of comovement.

As shown in Figure 7, there was a significantly strengthened linkage effect of the USD in the international FX network during the U.S. subprime mortgage crisis. We analyzed the rolling window based on a time period of 12 months in line with Figure 5, doing so in order to illustrate the short-term change of the structural information in the international monetary system. Compared to Figure 4, where the USD only linked to one currency, the worldwide spread of the subprime crisis undoubtedly contributed to a remarkable increase in the linkage effect of the USD. In the empirical process, it is reflected in a reducing average path length and an increasing degree with respect to the topological properties of the USD in the MST. This discovery provides strong practical evidence for the connection between the structural linkages and the real international currency markets. More specifically, the subprime crisis results in an apparent reinforcement of the linkage effect of the USD in terms of the degree and the average path length.

## 5. Conclusions

We, in this paper, modeled currency networks by using REER (real effective exchange rate) instead of the bilateral exchange rate to overcome the confusion in selecting base currencies. We examined the linkage effects that appeared in the real effective exchange rate (REER) among a group of 61 major currencies during the period of 1994 to 2014. The correlation matrix and distance matrix were used to construct topological pictures of sample currencies. With this methodology we were able to analyze the structural (long term) and dynamical (short term) linkages among currencies. The use of the MST method was shown to be valuable, as it provided a better understanding of the interdependence and linkage effects in currency networks, and the use of the rolling-window method tested the robustness of our results. Because currency networks represented the linkage effects among currencies, it is necessary to construct networks based on the true value of each currency. Bilateral exchange rate data showed only the relative value based on a certain type of numeraire, while the value of each currency moved up or down depending on the volatility of the numeraire's value. In other words, bilateral exchange rate data did not represent the true value of each currency. However, the REER data was calculated as weighted

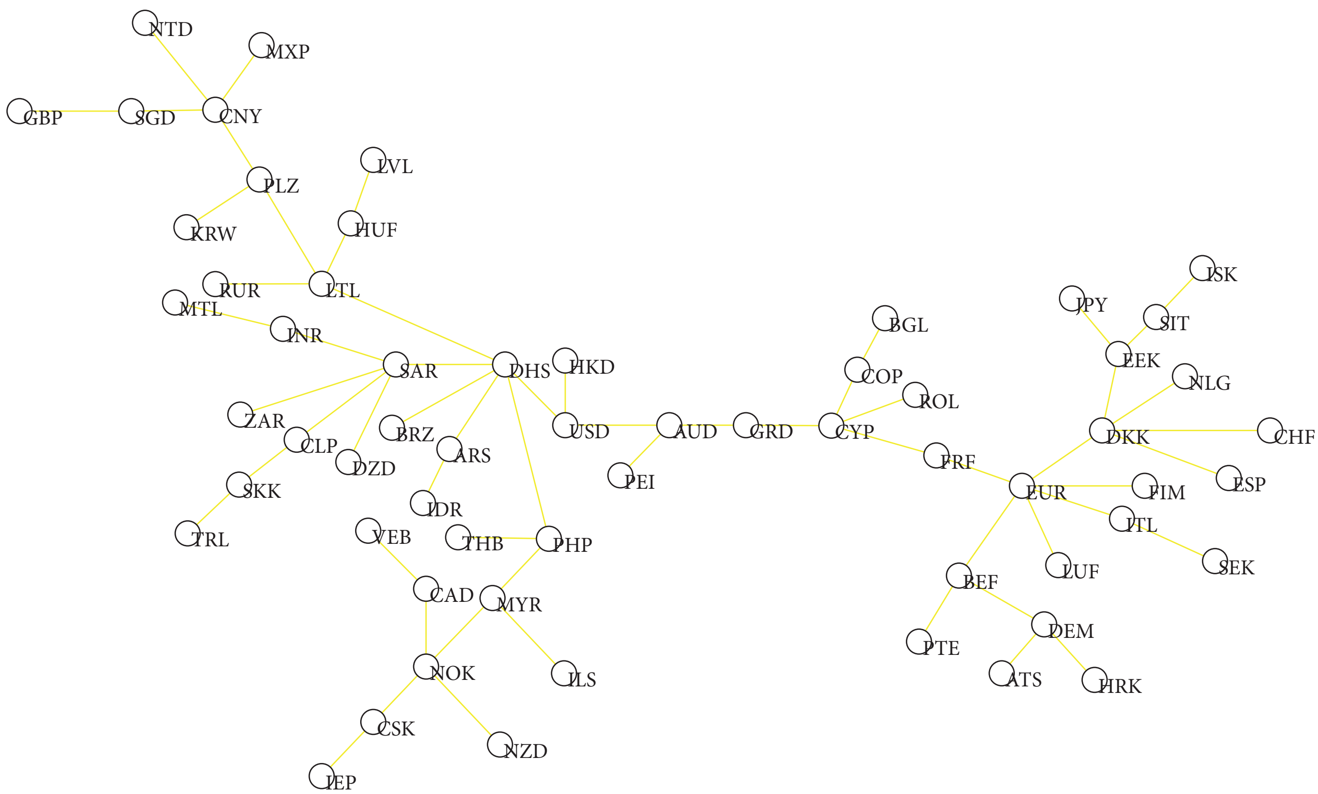


FIGURE 6: MST of 61 currencies in May 1997, as a representative of the period during Asian financial crises (window length = 12 months).

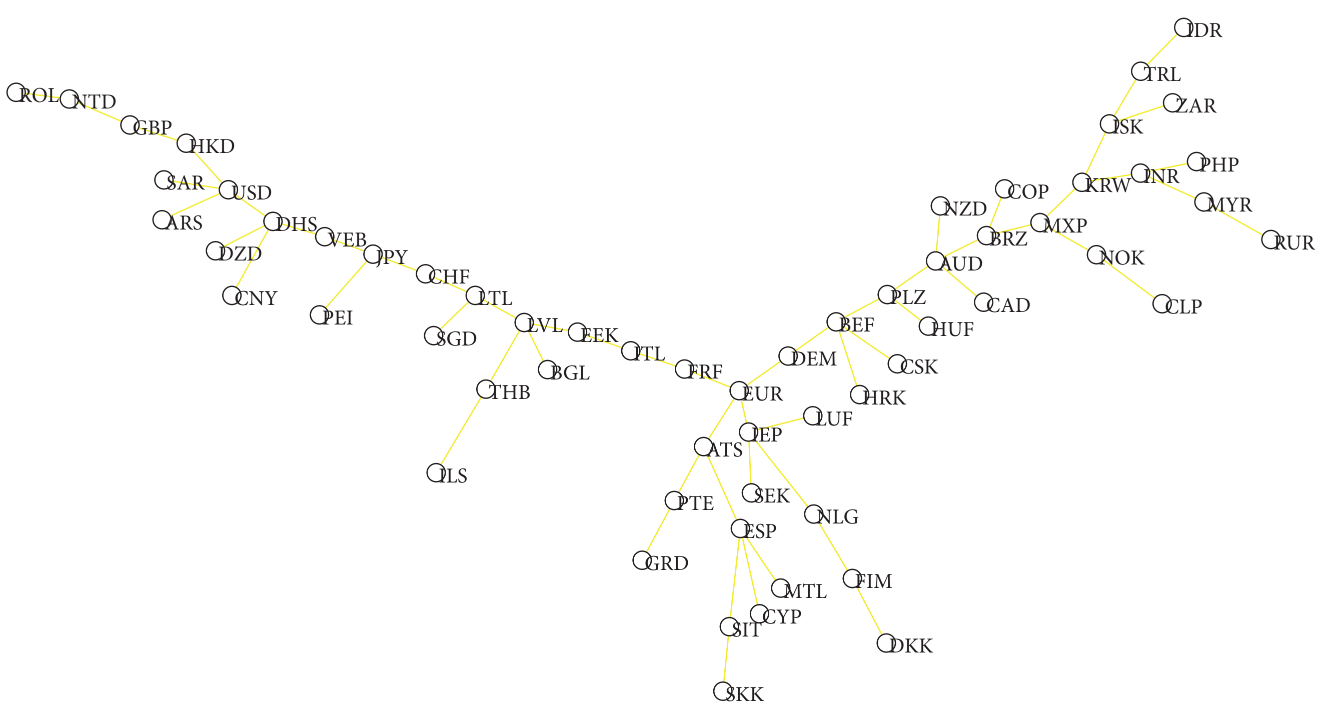


FIGURE 7: MST of 61 currencies in October 2008, as a representative of the period during US financial crises (window length = 12 months).

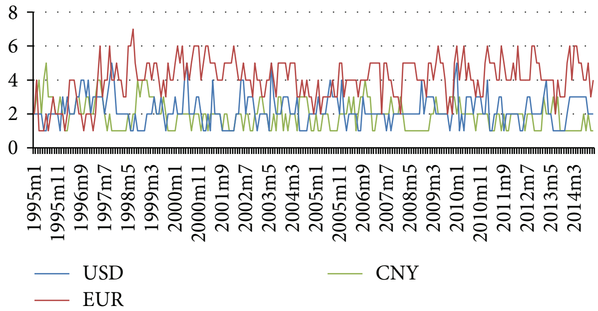


FIGURE 8: The number of links with respect to USD, EUR, and CNY (window length = 12 months).

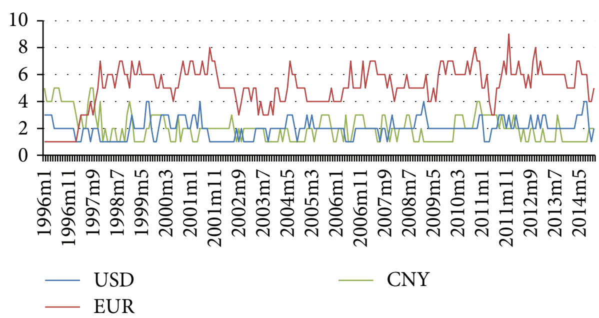


FIGURE 9: The number of links with respect to USD, EUR, and CNY (window length = 24 months).

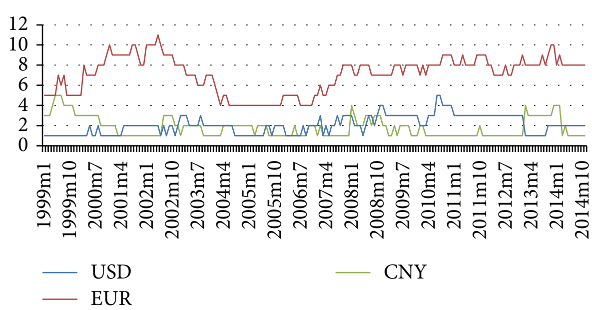


FIGURE 10: The number of links with respect to USD, EUR, and CNY (window length = 60 months).

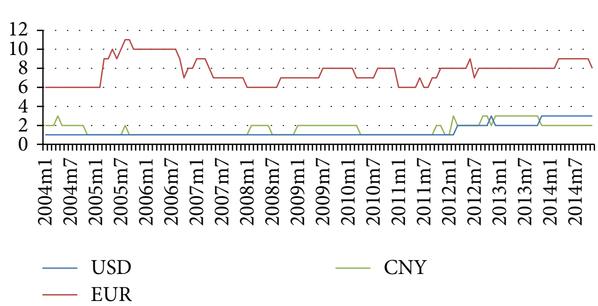


FIGURE 11: The number of links with respect to USD, EUR, and CNY (window length = 120 months).

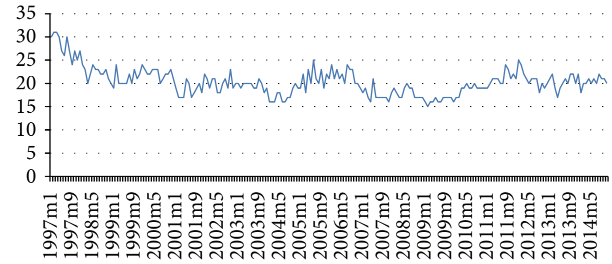


FIGURE 12: The number of total links with respect to 10 regions in East and Southeast Asia (window length = 36 months).

averages of bilateral exchange rates. Economists often use REER data to reflect the competitiveness of currencies. The REER data was able to reflect the true value of each currency, so it was more appropriate as a means to represent the linkage effects among currency networks. Our results suggest that it is more appropriate to represent the linkage effects of currency networks using REER data than to use bilateral exchange rate data.

## Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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