Expert Systems With Applications 46 (2016) 164–179

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Tail dependence structure of the foreign exchange market: A network view

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ARTICLE INFO

Keywords:
Dependence structure
Foreign exchange market
Network
Copula
Cluster analysis
Community structure

ABSTRACT

Tail dependence of financial entities describes when the price of one financial asset has an extreme fluctuation (e.g., price sharply rises or falls), the degree of its effect on the price fluctuation of another asset. Under the background of the global financial crisis, tail dependence structure of financial entities plays an important role in financial risk management, portfolio selection, and asset pricing. In this paper, we propose a concept of tail dependence networks to investigate the tail dependence structure of the foreign exchange (FX) market. Lower- and upper-tail dependence networks for 42 major currencies in the FX market from 2005 to 2012 are constructed by combing the symmetrized Joe-Clayton copula model and two filtered graph algorithms, i.e., the minimum spanning tree (MST) and the planar maximally filtered graph (PMFG). We also construct the tail dependence hierarchical trees (HTs) associated with the MSTs to analyze the currency clusters. We find that (1) the two series of lower- and upper-tail dependence coefficients present different statistical properties; (2) the upper-tail dependence networks are tighter than the lower-tail dependence networks; and (3) different currency clusters, cliques and communities are respectively found in the two tail dependence networks. The key empirical results indicate that market participants should consider the different topological features at different market situations (e.g., a booming market or a recession market) to make decisions on the investing or hedging strategies. Overall, our obtained results based on the tail dependence networks are new insights in financial management and supply a novel analytical tool for market participants.

1. Introduction

The dependence structure of financial markets is a key and debatable issue for financial economists, regulators and investors. It is the useful and important information for some financial activities, such as international portfolio's diversification and risk management, derivative pricing, and market integration (Buccheri, Marmi, & Mantegna, 2013). For example, how to select financial assets in the international portfolio diversification is the crucial step, which needs to examine the dependence of financial asset returns and check whether they have the dependence hierarchical or clustering structure. As such, a growing number of methods are developed to capture the dependence structure among different financial asset returns, while the dependence (or correlation) network analytical tool is one of the most popular and widely used approaches (see, e.g., Brida, Gómez, & Risso, 2009; Brida & Risso, 2010; Fenn et al., 2012; Kwapień & Drożdż, 2012; Kwapień, Gworek, & Drożdż, 2009; Mantegna, 1999; Tumminello, Lillo, & Mantegna, 2010; Wang, Xie, Chen, & Chen, 2013a; Wang, Xie, Han, & Sun, 2012). Different approaches can be used to build the dependence network, such as the minimum spanning tree (MST) approach (Mantegna, 1999), the planar maximally filtered graph (PMFG) method (Tumminello, Aste, Matteo, & Mantegna, 2005), and the correlation threshold method (Boginski, Butenko, & Pardalos, 2005; Onnela, Kaski, & Kertész, 2004), which are designed to select or filter the information presented in the dependence (or correlation) matrix. In other words, before constructing the financial networks, one should build the dependence matrix of the financial asset returns by the dependence measure, while the common practice of the dependence measure is chosen as the Pearson's correlation coefficient (PCC). Although PCC is easy to calculate and widely used, some questions are posed on the practice of using PCC as a universal dependence measure (see, e.g., Rachev, Fabozzi, & Menn, 2005; Wang et al., 2012; Zebende, 2011; Zhou & Gao, 2012). There are at least two drawbacks for PCC as follows. (1) The theoretical assumption of PCC is that the joint distributions of time series

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http://dx.doi.org/10.1016/j.eswa.2015.10.037
0957-4174/

obey Gaussian distribution. However, a large deal of evidence shows that the dependence between different financial asset returns is non-Gaussian (see, e.g., Bae, 2003; Durante, Foscolo, Jaworski, & Wang, 2014; Wang, Xie, Zhang, Han, & Chen, 2014). A good instance is that the dependence of financial asset returns during a recession is larger than during a boom (Zhou & Gao, 2012). Besides, many studies report that the dependence of financial markets comes to a remarkable peak during the largest market shocks and financial crises (see, e.g., Aste, Shaw, & Di Matteo, 2010; Podobnik, Wang, Horvatic, Grosse, & Stanley, 2010; Wang, Xie, Chen, Yang, & Yang, 2013b). (2) PCC is defined to quantify the linear correlation for the whole range of sample. It ignores the fact that the real world data are characterized by a high level of heterogeneity (Wang et al., 2013b). Namely, it neglects the difference between extreme and commonplace observations. It is a fact that as the frequency of financial crisis doubled in recent years, the extreme returns of financial time series occurred increasingly. Therefore, PCC may lose effectiveness and be misleading if the investigated asset returns are heterogeneous and the extreme returns show different patterns of dependence from the remaining returns (Zhou & Gao, 2012). In a word, the previous dependence network methods cannot accurately detect the dependence structure of financial markets, especially during the financial crises (e.g., US sub-prime crisis, 2008 financial crisis, and European debt crisis).

To overcome the shortcomings of linear correlation functions (e.g., PCC), scholars resort to a powerfully and widely used tool—copulas proposed by Sklar's (1959). Copulas are flexible and effective tools to measure dependence structure between two or more variables and model any type of multivariate distributions, which go beyond the linear correlation. Specifically, they allow for the tail dependence that represents the level of dependence among the tails of financial asset distributions (Sun, 2013; Zhou & Gao, 2012). In detail, tail dependence refers to the level of dependence in the lower and upper quadrant tails of a bivariate distribution, so it is a suitable measure of the dependence of extreme events. That is to say, tail dependence can be divided into two measures, namely the lower-tail dependence and upper-tail dependence, which are used respectively to investigate the joint extreme events in financial asset returns during the market downturns and market upturns (Hu, 2010). However, in the common practice of measuring dependence, people usually ignore the extreme returns that hide in the tails and the tail dependence among financial asset returns, which is dangerous for investment portfolios and other financial activities especially during the market downturns. So, more attentions should be paid to the tail dependence of financial markets. Unfortunately, to the best of our knowledge, very little of the existing research considers the tail dependence of the foreign exchange (FX) market from a network point of view.

Therefore, the aim of this paper is to propose a concept of tail dependence network by combing copulas and two network methods (MST and PMFG) for investigating the tail dependence structure of the FX market. We focus our study on the topology and clustering of tail dependence networks (i.e., lower-tail dependence network and upper-tail dependence network) of the FX market. We choose the FX market as the research object because it is the largest and most liquid financial market that directly or indirectly influences all other financial markets (Wang et al., 2014), and thus is a good representative for financial markets. In practical terms, we select the daily FX rates of the set of 42 major currencies in the FX market during the period 2005–2012 as the empirical data. The procedure of constructing the lower- and upper-tail dependence networks mainly consists of three steps.

Firstly, we compute the lower- and upper-tail dependence coefficients among 42 major currencies by a copula method. In this step, we first use the AR(1)-GARCH(1,1)-*t* model to characterize the marginal distributions of FX rate returns and then employ the symmetrized Joe-Clayton (SJC) copula proposed by Patton (2006) to calculate the lower- and upper-tail dependences. The motivations that lead us to choose the SJC copula to analyze the tail dependence structure of the FX market can be summarized as follows (Sun, 2013; Zhou & Gao, 2012). (1) SJC is a flexible copula approach to modeling the tail dependence because it can accommodate different types of dependence patterns that range from tail dependence to tail independence for both the lower and upper tails. (2) It allows for the asymmetric tail dependence and nests symmetry as a special case. More recently, the SJC copula has been widely applied in finance and economics (Basher & Nechi, 2014; Hammoudeh, Mensi, Reboredo, & Nguyen, 2014; Hoesli & Reka, 2015; Huang & Wu, 2015; Jammazi, Tiwari, Ferrer, & Moya, 2015; Ning, Xu, & Wirjanto, 2015; Yang & Hamori, 2014a). For example, Basher and Nechi (2014) study the tail dependences across Gulf Arab stock markets by the SJC copula and find that the lower-tail dependence is larger than the upper-tail dependence. Yang and Hamori (2014a) use the SJC copula to examine the tail dependence structure between gold prices and FX rates and observe that the upper-tail dependences of GBP/gold and JPY/gold are greater than the lower-tail dependences. Hoesli and Reka (2015) investigate the tail dependences between REIT and stock markets by the SJC copula and further research their contagion channels. Jammazi et al. (2015) analyze the tail dependences between stock and government bond returns for various countries and find that the tail dependences for most countries are asymmetric. From the aforementioned literature, we conclude that the JSC copula is a powerful tool to investigate the tail dependence structure of financial entities, which motives our choice for the SJC copula.

Secondly, on basis of the lower- and upper-tail dependence coefficients of the set of 42 currencies in the FX market, we construct the lower- and upper-tail dependence matrices, which are denoted as $\mathbf{T}^L$ and $\mathbf{T}^U$, respectively. Then, we transform the two tail dependence matrices into lower- and upper-tail distance (or dissimilarity) matrices, which are labeled as $\mathbf{D}^L$ and $\mathbf{D}^U$, respectively.

Finally, we transform the two tail distance matrices into lower- and upper-tail dependence networks by the MST and PMFG approaches, which are respectively called as lower- and upper-tail dependence MSTs and PMFGs. The choice of the MST and PMFG methods is motivated by the following reasons. On the one hand, the MST is a simple and robust method, which connects N nodes with $N-1$ stronger edges such that no loops are produced (Onnela, Chakraborti, Kaski, Kertesz, & Kanto, 2003; Wang et al., 2013a). On the other hand, the PMFG maintains the hierarchical structure of the MST but contains more information in comparison to the MST, which links N nodes with $3(N-2)$ edges (Tumminello et al., 2005). At the same time, we also present the lower- and upper-tail dependence hierarchical trees (HTs) associated with the MSTs to analyze the hierarchical structure of the FX market. Since Mantegna (1999) proposes the MST and Tumminello et al. (2005) develop the PMFG to study the dependence structure of financial entities, these two approaches are frequently chosen for construing financial networks (see, e.g., Birch, Pantelous, & Soramäki, 2015; Ji & Fan, 2014; Mai, Chen, & Meng, 2014; Matesanz & Ortega, 2014; Matesanz, Torgler, Dabat, & Ortega, 2014; Wang & Xie, 2015; Wang et al., 2014; Yan, Xie, & Wang, 2015). For instance, Matesanz and Ortega (2014) investigate the co-movements of 28 major currencies in the period of 1992–2002 in the FX market via combining the phase synchronous coefficient and MST. Ji and Fan (2014) study the topological network of 24 major crude oil markets from 2000 to 2011 by using the MST and HT tools and find that the global crude oil markets are clustered by geographical and organizational features. Matesanz et al. (2014) construct the HT and MST network for a sample of 32 commodity prices during the period 1993–2010 to examine the co-movement of commodity markets. Mai et al. (2014) analyze the constituent stocks of China Securities Index 300 (CSI 300) from 28 September 2009 to 30 March 2012 and build the PMFG network for the CSI 300 market, in which the CSI 300 market is found as a scale-free network. Wang and Xie (2015) construct the HT, MST and PMFG networks of 20 country indices in international real estate securities markets from 2006 to 2012 to study the corresponding hierarchical structure, clustering structure and community structure. Yan et al. (2015) examine the topological stability of stock market networks by identifying the MST and PMFG networks. Although many new developments and outcomes are obtained in the existing literature about the MST and PMFG networks, somewhat surprisingly, the concept of tail dependence networks has never been proposed, which motives us for this research.

Overall, compared to previous works on the dependence networks, the proposed lower- and upper-tail dependence networks have several outstanding advantages. (1) The proposed networks take into account the tail dependence of financial agents and can capture the heterogeneous and nonlinear features and tail risks of asset returns. (2) Our primary empirical results show that despite the lower- and upper-tail dependence networks look similar, different topological features (e.g., clusters and communities) exist in the two tail dependence networks. However, the existing literature on the dependence networks did not uncover these differences. (3) Our empirical outcomes suggest that market participants in the FX markets should adjust their investing or hedging strategies at different market situations under the guide of the tail dependence networks, which is a new contribution in the literature of financial networks.

In addition, our proposed tail dependence networks at least have three potential applications in the field of expert and intelligent systems. The first potential application is that the proposed tail dependence networks tool can be integrated into the FX trading systems. The FX trading systems with the embedded tail dependence networks is useful for market participants to construct FX portfolio and forecast the FX rates. Designing and constructing a financial decision-making platform based on the tail dependence networks is the second possible application. This proposed platform maps the complex financial systems and permits investors or hedgers to make network- and data-based decisions. The finial conceivable application is to design and build an early warning system (ESW) on the FX markets from a macro-perspective. Based on the ESW, one may predict the extreme events and tail risks by investigating the changes of topological properties of tail dependence networks.

The rest of this paper is organized as follows. In Section 2, we present lower- and upper-tail dependence networks by combing copulas and two network methods (MST and PMFG). In Section 3, we show the empirical data and main empirical results. Finally, we draw conclusions and present some future works in Section 4.

2. Methodology

In this section, we first describe the calculation of tail dependence coefficients, which consists of the copula functions, the model for marginal distributions, the SJC copula model, and the estimation of parameters. Then, we present the basics of construction of lower- and upper-tail dependence networks based on the MST and PMFG methods. For the first applications of MST and PMFG to financial markets and a more detailed description, see Mantegna (1999) and Tumminello et al. (2005).

2.1. Copula functions

Copula functions are flexible and useful tools to investigate the dependence structure of a multivariate distribution. A d-dimensional copula is a multivariate cumulative distribution function (CDF) with standard uniform marginal distributions (Aloui, Ben Aïssa, & Nguyen, 2013). Assume $X=(X_1, X_2, ..., X_d)$ is a random vector, with a joint CDF F and marginal CDFs $F_1, F_2, \dots, F_d$. According to Sklar's (1959) theorem, there exists a copula function C: $[0, 1]^d \rightarrow [0, 1]$ such that:

$$F(x_1, \dots, x_d) = C(F_1(x_1), \dots, F_d(x_d)). \tag{1}$$

Copula functions supply a convenient way to create a multivariate joint distribution by first modeling the univariate marginal distributions and then examining the dependence structure of a multivariate random variable (Yang & Hamori, 2014b). To be simple enough, in this paper, only the bivariate case are considered. Tail dependence, a useful dependence measure described by copulas, quantifies the probability that both variables are in their lower or upper joint tails (Ning, 2010). In general, two measurements of tail dependence are used to examine the tail dependence, i.e., lower- and upper-tail dependence coefficients, which are very helpful to detect the trend of financial markets to recession or brisk.

Let X and Y be two random variables with marginal CDFs F_X and F_Y, respectively, the lower- and upper-tail dependence coefficients are defined as

$$\tau^L = \lim_{\varepsilon\to 0} \Pr[Y \le F_Y^{-1}(\varepsilon) | X \le F_X^{-1}(\varepsilon)] = \lim_{\varepsilon\to 0} \frac{C(\varepsilon, \varepsilon)}{\varepsilon}, \tag{2}$$

$$\tau^U = \lim_{\varepsilon\to 1} \Pr[Y > F_Y^{-1}(\varepsilon) | X > F_X^{-1}(\varepsilon)] = \lim_{\varepsilon\to 1} \frac{1-2\varepsilon + C(\varepsilon, \varepsilon)}{1-\varepsilon}, \tag{3}$$

where ε is the probability, τ^L and $\tau^U \in [0, 1]$. If τ^L or τ^U is positive, the two random variables X and Y are lower-tail dependence or upper-tail dependence; otherwise, there are lower-tail independence or upper-tail independence. Further detailed descriptions on copula functions can be seen in Joe (1997) and Nelsen (2006).

2.2. Model for marginal distributions

Some stylized facts of financial asset returns, such as fat-tails, autocorrelations, and volatility clustering, are well documented in previous literature. The GARCH model is the most popular method to model financial time series and capture their stylized features like volatility clustering. In addition, Bollerslev (1987) and Ning (2010) find that the univariate distribution of the daily FX rate returns can be well fitted by the Student's t-distribution. Therefore, following Patton (2006), Dias and Embrechts (2010) and Wang et al. (2014), we employ the AR(1)-GARCH(1,1)-t model to characterize the marginal distributions of the FX rate returns. The model is expressed as follows:

$$r_{i,t} = \mu_i + \varphi_{1,i} r_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

$$z_{i,t}|I_{t-1} = \sqrt{\frac{\upsilon_i}{\sigma_{i,t}^2(\upsilon_i - 2)}} \cdot \varepsilon_{i,t},\ z_{i,t} \sim iid\ t(\upsilon_i), \tag{5}$$

$$\sigma_{i,t}^2 = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2, \tag{6}$$

where $r_{i,\,t}$ is the FX rate returns of currency i at time t, μ_i and $\varepsilon_{i,\,t}$ are the mean and error term in the conditional mean equation,respectively, $\varphi_{1,\,i}$ is the autoregressive (AR) coefficient with the order of one, $z_{i,\,t}$ follows a Student's t-distribution, $\sigma_{i,t}^2$ is the conditional variance of the error term $\varepsilon_{i,\,t}$ with the following conditions: $\omega_i > 0, \alpha_i > 0, \beta_i > 0$, and $\alpha_i+\beta_i < 1$, υ_i is the degree of freedom of the Student's t-distribution, and I_{t-1} is the information set at time $t-1$. In this study, we set the order of AR and the lag orders of the GARCH model all to be one, which is in accordance with the Brooks's (2008) statement that the volatility clustering in financial asset returns can be sufficiently described by a GARCH-family model with the lag order of one.

2.3. Symmetrized Joe-Clayton (SJC) copula model

After obtaining the marginal distribution for each FX rate returns, we use a copula function to compute the tail dependence. According to Joe (1997) and Nelsen (2006), many copulas can be chosen to model the dependence of financial asset returns. Two frequently used models are the Gaussian and Student's t copulas. However, the Gaussian copula shows tail independence (i.e., τ^L and τ^U are both equal to zero), while the Student's t copula exhibits symmetric tail dependence (i.e., lower- and upper-tail dependences are the same). Another two copulas are the Gumbel and Clayton copulas, which can be used to analyze the tail dependence. These two copulas are also not chosen in this paper because the Gumbel copula can be only used to measure the upper-tail dependence while the Clayton copula can be only used to calculate the lower-tail dependence. A good choice is the Symmetrized Joe-Clayton (SJC) copula because it has the ability to model asymmetric tail dependence (i.e., lower- and upper-tail dependences). For instance, Patton (2006) uses the SJC copula to examine the tail dependence between two FX rates. Actually, the SJC copula proposed by Patton (2006) is the modification and extension of the Joe-Clayton (JC) copula. Given two standard uniform variables u and v (which stand for two different currencies), the JC copula (Joe, 1997) is defined as

$$C_{JC}(u, v|\tau^L, \tau^U) = 1 - \left(1 - \left[(1-(1-u)^\kappa)^{-\gamma} + (1-(1-v)^\kappa)^{-\gamma} - 1\right]^{-1/\gamma}\right)^{1/\kappa}, \tag{7}$$

where $\kappa = 1/\log_2(2-\tau^U)$, $\gamma = -1/\log_2(\tau^L)$. τ^L and $\tau^U \in (0, 1)$ are the lower- and upper-tail dependence coefficients respectively. The SJC copula (Patton, 2006) is expressed as

$$C_{SJC}(u, v|\tau^L, \tau^U) = 0.5\left[C_{JC}(u, v|\tau^L, \tau^U) + C_{JC}(1-u, 1-v|\tau^L, \tau^U) + u + v - 1\right]. \tag{8}$$

As presented by Sun (2013), the density of SJC copula can be derived as

$$c_{SJC}(u, v|\tau^L, \tau^U) = \frac{\partial^2 C_{SJC}(u, v|\tau^L, \tau^U)}{\partial u \partial v} = 0.5\left[\frac{\partial^2 C_{JC}(u, v|\tau^L, \tau^U)}{\partial u \partial v} + \frac{\partial^2 C_{JC}(1-u, 1-v|\tau^L, \tau^U)}{\partial(1-u)\partial(1-v)}\right], \tag{9}$$

which allows the lower- and upper tail dependences to be estimated, following the inference-function-for margins (IFM) approach proposed by Joe and Xu (1996) which is presented in the next section.

2.4. Estimation of copula parameters

The copula parameters can be estimated by two steps, the first for the marginal distributions and the second for the copula functions. Two widely used methods are the IFM and the exact maximum likelihood (EML). Following Lai (2009), Wang, Chen, and Huang (2011) and Wang et al. (2014), we employ the IFM to estimate the copula parameters rather than the EML, because the later needs more computation than the former. The two-step estimations of the IFM are presented as follows:

Step 1. The parameters in the marginal distributions are estimated by the maximum likelihood as

$$\hat{\theta}_i = \arg\max \sum_{t=1}^{T} \ln f_i(z_{i,t}; \theta_i), \tag{10}$$

where $f_i(\cdot)$ refers to the marginal density of the FX rate returns of currency i, and θ_i is the parameter set of returns of currency i.

Step 2. Given θ_u and θ_v for two different currencies, the copula parameters can be estimated as

$$\hat{\theta}_c = \arg\max \sum_{t=1}^{T} \ln c_{SJC}(F_u(z_{u,t}; \theta_u), F_v(z_{v,t}; \theta_v); \theta_c). \tag{11}$$

2.5. Lower- and upper-tail dependence networks

Once we obtain the lower- and upper-tail dependence coefficients between any two currencies in the FX market, we then build $N \times N$ lower- and upper-tail dependence matrices $\mathbf{T}^L$ and $\mathbf{T}^U$ with elements τ_{ij}^L and τ_{ij}^U for currencies i and j, respectively, where N is the number of currencies ($N = 42$, in our case), and $1 \le i, j \le 42$. According to the original application of the MST introduced by Mantegna (1999), the dependence coefficient should be transformed into a distance (or dissimilarity) measure. Following Durante et al. (2014), we transform the lower- and upper-tail dependence matrices $\mathbf{T}^L$ and $\mathbf{T}^U$ into two tail distance matrices $\mathbf{D}^L$ and $\mathbf{D}^U$ by the distance measures $d_{ij}^L = \sqrt{1-\tau_{ij}^L}$ and $d_{ij}^U = \sqrt{1-\tau_{ij}^U}$, respectively. Based on the two distance matrices $\mathbf{D}^L$ and $\mathbf{D}^U$, we can obtain the lower- and upper-tail dependence networks of the FX market filtered by the MST and PMFG methods, which are respectively called as lower- and upper-tail dependence MSTs and PMFGs. That is to say, four tail dependence networks are gained in our study.

The tail dependence MST network filters the tail distance matrix and links all N nodes (currencies) with $N-1$ stronger edges such that the sum of all currency distances is the minimum. In other words, the construction idea behind MST is to reduce the number of $N(N-1)/2$ elements originally contained in the tail distance matrix to only the $N-1$ most important links. In this study, we use the Kruskal's (1956) algorithm to construct the MST network. Here we show a brief introduction of the procedure of the MST as follows (Aste et al., 2010):

Step 1. Create an order list of edges e_{ij} (which contains $N(N-1)/2$ edges, i.e., $N(N-1)/2$ elements in the tail distance matrix), ranking them by non-decreasing tail distance d_{ij}^L (or d_{ij}^U).

Step 2. Take the first element (i.e., the edge with the smallest tail distance) in the ranked list and add the edge into a graph G.

Step 3. Take the next element and add the edge if and only if the graph acquired after the edge insertion is still a forest or a tree; otherwise discard the element.

Step 4. Repeat Step 3 until all elements in the ordered list are used up.

The tail dependence PMFG network keeps the same powerful filtering characters of the tail MST network but contains extra links, loops, and cliques, and thus more complex than the tail MST network. That is, the PMFG is a network with loops whereas the MST is a tree without loops. Notable differences between the MST and PMFG networks are summed up as follows. (1) The topological constraint (i.e., the condition at Step 3 in the procedure) for the new inserted edge is different. The topological constraint of the MST network is that the resulting graph is still a forest or a tree (i.e., no loops are produced in the resulting graph), while the topological constraint of the PMFG network is that the resulting graph can still be embedded on a plane or a sphere (Tumminello et al., 2010), i.e., topological surfaces with fixed genus $g = 0$.[1] (2) The number of edges is different. The MST connects N nodes with $N-1$ edges, while the PMFG links N nodes with $3(N-2)$ edges. Namely, the PMFG has 3 times the number of edges as the MST.

Another difference is that the PMFG contains 3-cliques and 4-cliques. In graph theory, an n-clique is a complete sub-graph on n vertices such that every two vertices in the sub-graph are linked by an edge. A clique in the financial network refers to a set of the financial assets whose price fluctuations show a similar behavior, i.e., a price change of one asset in the clique can possibly influence the price behavior of all other assets in this clique (Boginski et al., 2005; Wang & Xie, 2015).

[1] Genus is a topologically invariant property of a surface defined as the largest number of nonintersecting simple closed curves that can be drawn on the surface without separating it. Roughly speaking, a genus of a surface is the number of holes in a surface. A plane or sphere has genus 0, and a torus has genus 1, etc. For a more detailed explication, see Tumminello et al. (2005, 2010) and Aste et al. (2010).

Table 1
42 currencies and respective symbols.

Continent	Currency	Symbol	Continent	Currency	Symbol
Africa	Egyptian Pound	EGP	Europe	Romanian New Leo	RON
	South Africa Rand	ZAR		Russian Rubles	RUB
Asia	Chinese Renminbi	CNY		Swedish Krona	SEK
	Indian Rupee	INR		Swiss Franc	CHF
	Indonesian Rupiah	IDR		Turkish New Lira	TRY
	Japanese Yen	JPY	Latin America	Argentinian Peso	ARS
	Malaysian Ringgit	MYR		Brazilian Real	BRL
	Pakistani Rupee	PKR		Chilean Pesos	CLP
	Philippines Peso	PHP		Colombian Peso	COP
	Singapore Dollar	SGD		Peruvian New Sole	PEN
	South Korean Won	KRW		Mexican Peso	MXN
	Taiwan Dollar	TWD	Middle East	Bahrain Dinar	BHD
	Thai Baht	THB		Israeli New Shekel	ILS
	Vietnamese Dong	VND		Jordanian Dinar	JOD
Europe	British Pound	GBP		Kuwaiti Dinar	KWD
	Czech Koruna	CZK		Saudi Arabian Riyal	SAR
	European Euros	EUR		United Arab Emirates Dirham	AED
	Hungarian Forint	HUF	North America	Canadian Dollar	CAD
	Icelandic Krona	ISK		US Dollar	USD
	Norwegian Krone	NOK	Oceania	Australian Dollar	AUD
	Polish Zloty	PLN		New Zealand Dollar	NZD

3. Empirical data and results

3.1. Empirical data

We analyze the FX rates of the set of 42 major currencies in the FX market from January 4, 2005 to December 31, 2012. The empirical data consist of the daily FX rates obtained from the website of the Pacific Exchange Rate Service (http://fx.sauder.ubc.ca/data.html). The choice of the numeraire (or the base currency) is a difficult and common problem in the FX market research because currencies in the FX market are priced against each other and thus there exists no independent numeraire (Keskin, Deviren, & Kocakaplan, 2011). People once considered the metals (e.g., the gold and silver) but dismissed them due to their high volatility. According to the recent works, there are two main ways to choose a suitable numeraire: one is to choose a minor currency that has little impact on the world economy, e.g., Keskin et al. (2011) take the Turkish New Lira (TRY) as the numeraire; and the other is to consider a currency basket that can reflect the whole changes of the world economy, such as the special drawing right (SDR). The SDR designed by the International Monetary Fund (IMF) is a reserve asset and a unit of account, which is also known as the “paper gold”. Therefore, like in Frankel and Xie (2010), Jang, Lee, and Chang (2011) and Wang and Xie (2013), we choose the SDR as the numeraire. The 42 currencies come from seven different continents or regions, and their corresponding symbols are organized in Table 1. As usual, the FX rate returns of currency i are calculated on a continuous compounding as $r_{i,t}=100\times(\ln P_{i,t}-\ln P_{i,t-1})$, where $P_{i,t}$ and $P_{i,t-1}$ are the daily FX rates of currency i on days t and $t-1$, respectively. After supplementing the missing data of several currencies in a few transaction days, we finally obtain 2003 log-returns for each currency.

We make a summary statistics of returns of 42 currencies during the analyzed period.[2] We find that the means of returns of 42 currencies are very small in relation to their standard deviations, presenting relatively high risks. Besides, we also find that skewness, leptokurtosis, and significant Jarque–Bera statistics (at 1% level) exist in the FX rate returns, which suggest that the FX rate returns’ unconditional distributions are asymmetric, fat-tailed, and non-Gaussian. From the results of the ARCH-LM test for conditional heteroscedasticity on the returns of 42 currencies, we observe that there is significant volatility clustering in each return series, implying that the GARCH model is suitable for modeling the FX rate returns.

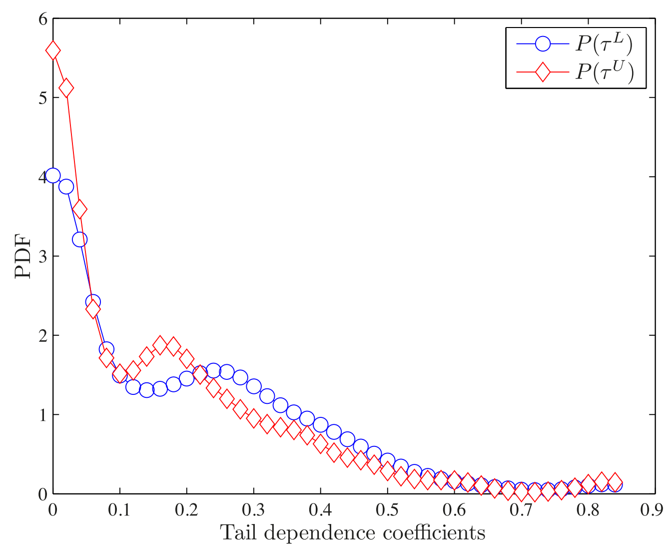

Fig. 1. Probability density functions (PDFs) of lower- and upper-tail dependence coefficients $\{\tau_{ij}^L;i<j\}$ and $\{\tau_{ij}^U;i<j\}$.

3.2. Statistics of tail dependence coefficients

In this subsection, we analyze the statistics of the non-diagonal and upper (or lower) triangular elements (i.e., tail dependence coefficients between any two currencies) in the tail dependence matrix. For both the lower- and upper-tail dependence coefficient series, there are 861 (i.e., $N(N-1)/2$) observations. By comparing the two series of tail dependence coefficients, we find that 278 pairs of observations are the same. Namely, about 32% of the lower-tail dependence coefficients are equal to the upper-tail dependence coefficients, while the rest (68%) of observations determine the difference of the dependence structure in the FX market. Therefore, to find the similarities and differences between the lower-tail and upper-tail dependence structures is an interesting and important work.

In Fig. 1, we present the probability density functions (PDFs) $P(\tau^L)$ and $P(\tau^U)$ of the elements $\{\tau_{ij}^L;i<j\}$ and $\{\tau_{ij}^U;i<j\}$ of the

[2] Due to space limitations, the detailed summary statistics are not presented in this paper, which can be available from the authors upon request.

Table 2
Descriptive statistics of lower- and upper-tail dependence coefficients $\{\tau_{ij}^L; i<j\}$ and $\{\tau_{ij}^U; i<j\}$.

	Mean	Minimum	Maximum	Standard deviation
Lower-tail	0.1624	8.2718e−025	0.8478	0.1841
Upper-tail	0.1416	5.1295e−026	0.8411	0.1735

lower- and upper-tail dependence matrices $\mathbf{T}^L$ and $\mathbf{T}^U$. One can observe that the two distributions are different except for the overlapped right-tails. This observation suggests that (1) the strong tail dependence structure of the FX market is stable; and (2) the difference between the two tail dependence structures is mainly reflected in the weak tail dependence structure that is unstable. That is to say, several strong dependences among some currencies do not change along with the market conditions ranging from the depression to the booming or vice versa, while majorities of weak dependences in the FX market are varying as the change of the market. Besides, the number (or the probability) of weak upper-tail dependences is greater than that of weak lower-tail dependences.

In Table 2, we show the basic descriptive statistics of lower- and upper-tail dependence coefficients $\{\tau_{ij}^L; i<j\}$ and $\{\tau_{ij}^U; i<j\}$. From Table 2, we can find that the values of mean and standard deviation of upper-tail dependence coefficients are both smaller than that of the lower-tail dependence coefficients, which implies that the whole dependences among currencies in the FX market during market downturns is stronger and more volatile than that during market upturns. Both the minimums of lower- and upper-tail dependence coefficients are close to zero, meaning that tail independence exists in the FX market. The coefficients between USD and CNY, and between JOD and AED are maximums of the lower- and upper-tail dependence coefficients respectively, which indicates that the above two pairs of currencies possess the strongest dependence in the FX market under different market situations. A possible interpretation of USD-CNY having the largest lower-tail dependence coefficient is that CNY is re-pegged to USD during 2008 financial crisis (i.e., market downturns).

3.3. Topological properties of tail dependence networks

Networks' topological properties determine the function of networks and affect their dynamic behavior. In the analysis of networks, two common topological features are the average length path and average clustering coefficient. We show a brief introduction of the two measures as follows.

Definition 1. Consider an un-weighted graph $G(V, E)$, where V is the set of vertexes and E is the set of edges. If vertexes v_i and v_j are directly connected, the path length l_{ij} between vertexes v_i and v_j is equal to 1; otherwise, it is defined as the length (or steps) of the shortest path between two vertexes v_i and v_j (Wang et al., 2014). The average path length (APL) is defined as the average length along the shortest paths for all possible pairs of network vertexes, i.e.,

$$L_{\mathrm{APL}} = \frac{2}{N(N-1)} \sum_{i<j} l_{ij}, \tag{12}$$

where N is the number of vertexes.

Definition 2. In an un-weighted graph $G(V, E)$, let k_i be the degree of vertex v_i (which means that vertex v_i has k_i neighbors in the set of vertexes Γ_i), $\langle k\rangle$ be the average degree of the graph G, and e_{ij} be an edge connecting vertexes v_i and v_j. If there are E_i edges among k_i vertexes, i.e., E_i=#$\{e_{jk}|v_j, v_k \in \Gamma_i, e_{jk} \in E\}$, the clustering coefficient C_i of vertex v_i is defined as

$$C_i = \frac{2E_i}{k_i(k_i-1)}, \tag{13}$$

where $k_i(k_i-1)/2$ is the number of edges that could exist among the vertices within the set Γ_i. The average clustering coefficient (ACC) proposed by Watts and Strogatz (1998) is defined as the average of clustering coefficients of all vertexes N, i.e.,

$$L_{\mathrm{ACC}} = \frac{1}{N} \sum_{i=1}^{N} C_i. \tag{14}$$

Table 3
The average degree $\langle k\rangle$, the average path length L_{APL}, and the average clustering coefficient L_{ACC} of lower- and upper-tail dependence MSTs and PMFGs, and a random graph.

	$\langle k\rangle$	L_{APL}	L_{ACC}
Lower-tail dependence MST	1.9524	5.5633	0
Upper-tail dependence MST	1.9524	6.0128	0
Lower-tail dependence PMFG	5.7143	3.1417	0.7062
Upper-tail dependence PMFG	5.7143	3.5436	0.6985
Random graph	5.7143	2.2451	0.0814

As for the economic interpretations of the aforementioned topological features, we show a short presentation as follows. In the financial network, the path length between two assets (e.g., currencies) means that one asset's price fluctuations need the number of other assets acted as the intermediaries, which can be transferred to another asset. Therefore, the average length refers to the average number of intermediates between any two assets, and characters the size of the network. Each asset and its directly connected assets make up a neighborhood group, while an asset's clustering coefficient in the financial network represents the level of cluster of the neighborhood group. So, the average clustering coefficient reflects the whole compactness of the network.

In Table 3, we present the computed results of the average degree $\langle k\rangle$, the average path length L_{APL}, and the average clustering coefficient L_{ACC} of lower- and upper-tail dependence MSTs and PMFGs. From the results of the average degree in Table 3, it can be found that on average, each vertex has only one or two neighbors in the tail dependence MST network, while in the tail dependence PMFG network it has five or six neighbors. Interestingly, the average path length of the upper-tail dependence networks is larger than that of the lower-tail dependence networks, indicating that the size of the former is greater than that of the later. The average clustering coefficient of the tail dependence MST network is equal to zero because the MST network has no loops. About the compactness of the network measured by the average clustering coefficient, the lower-tail dependence PMFG network is a little tighter than the upper-tail dependence PMFG network. As reported by Watts and Strogatz (1998), small-world properties are common found in the real-world networks, such as the collaboration network of actors, the electrical power grid network, and the neuron network of the nematode worm. The so-called small-world network is a kind of graph in which majorities of vertexes are not neighbors of one another, but majorities of vertexes can be reachable from all the rest vertexes by a small handful of hops or steps. To examine whether the tail dependence PMFGs are small-world networks, we create a random graph with the same number of vertexes (N) and the average degree ($\langle k\rangle$), and present its results of average path length and average clustering coefficient in Table 3. Watts and Strogatz (1998) state that in a small-world network, its average path length is close to that of a random graph which has the same network parameters (i.e., vertexes and the average degree) as the investigated network, while the average clustering coefficient of a small-world network is far larger than a random graph. From this, we can come to a conclusion that the two tail dependence PMFGs are small-world networks.

In financial markets, the price fluctuations of one asset usually have an influence on other asset's price behavior, while the strength of influence may be different for different assets. To quantify how strongly a given vertex (asset) influences others in the financial

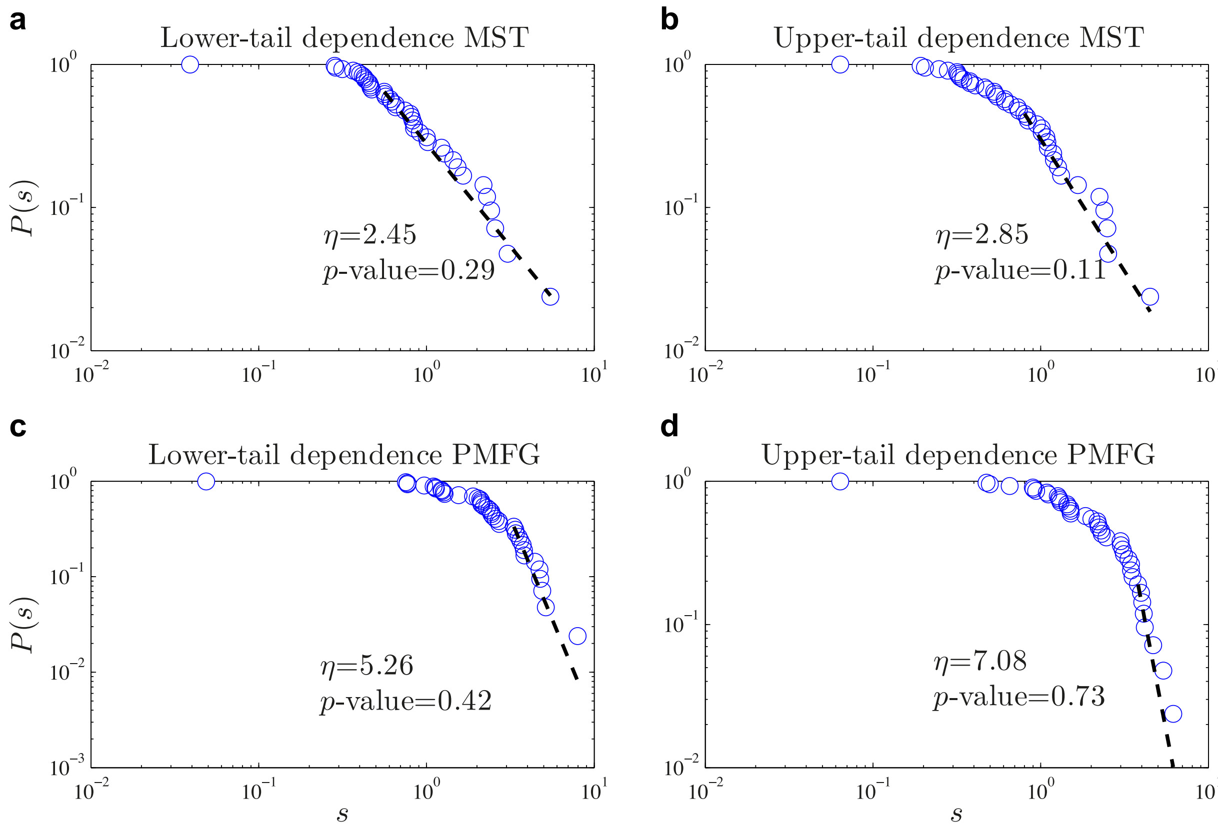

Fig. 2. Log–log plots of influence-strength distribution $P(s)$ versus the influence-strength s. Panels (a)–(d) represent the power-law exponent η and the corresponding p-Value for the lower- and upper-tail dependence MSTs and PMFGs, respectively. In each panel, the dashed line shows that the power-law fit to the distribution tail. As proposed by Clauset et al. (2009), if the p-Value is greater than 0.1, the power-law hypothesis is accepted for the test data; otherwise it is rejected.

network, we introduce a physical quantity proposed by Kim, Lee, Kahng, and Kim (2002), called the influence-strength (IS).

Definition 3. In a weighted graph $G(V, W)$, let Γ_i be a set of vertexes connected to the vertex v_i. The influence-strength is defined as the sum of the weights of all edges incident upon a given vertex v_i (Kim et al., 2002), i.e.,

$$s_i = \sum_{v_j \in \Gamma_i} \tau_{ij} = \sum_{v_j \in \Gamma_i} 1 - d_{ij}^2, \tag{15}$$

where τ_{ij} stands for the lower- or upper-tail dependence coefficient between currencies i and j, while d_{ij} is the corresponding distance.

The quantity of influence-strength not only considers the number of assets that directly link to an asset i, but also takes into account their strength of the dependence. The larger influence-strength that an asset (vertex) has, the greater influence of it on other assets (vertexes) is.

As reported by Kim et al. (2002), the distribution of influence-strength usually follows a power-law, i.e.,

$$P(s) \sim s^{-\eta}, \tag{16}$$

where s is the influence-strength, and η is the power-law exponent.

In Fig. 2, we draw the log–log plots of the distribution of influence-strength versus the influence-strength for the four tail dependence networks. To detect the power-laws of the influence-strength, we adopt a powerful tool proposed by Clauset, Shalizi, and Newman (2009), which is a combination of maximum-likelihood fitting approaches and goodness-of-fit tests on basis of the Kolmogorov–Smirnov statistic and likelihood rates. Based on the method developed by Clauset et al. (2009), we compute power-law exponents and the corresponding p-Values, and show them in Fig. 2. Clauset et al. (2009) suggest that if the estimated p-Value is larger than 0.1, we can accept the power-law hypothesis for the empirical data. From Fig. 2, we can see that all the four p-Values are greater than 0.1, which indicates that the influence-strength distributions of the four tail dependence networks for the FX market obey the power-law. The power-law distribution of influence-strength means that a few assets (vertexes) always have the larger influence-strength that significantly affect other assets (vertexes), whereas most assets' (vertexes') influence-strength is too weak to influence other assets (vertexes). Besides, in Fig. 2, one can find that the power-law exponents of lower-tail dependence MST and PMFG networks are respectively smaller than that of upper-tail dependence MST and PMFG networks. This finding implies that the influence-strength distribution of upper-tail dependence networks is more uniform than that of lower-tail dependence networks; on the other hand, it suggests lower-tail dependence networks have more assets (vertexes) with a large influence-strength than upper-tail dependence networks.

In Table 4, we list the top and the bottom five currencies ranked by the influence-strength in the four tail dependence networks.[3] From Table 4, one can find that USD has the greatest influence-strength in the four networks, suggesting that USD is the well-deserved dominant currency in the world. It is a surprise that JOD has the second ranked influence-strength in the two tail dependence MST networks. It would make sense that the monetary policy of Jordan is a fixed exchange rate pegged to USD, so the influence of JOD may be ascribed to the influence of USD. In the two tail dependence PMFG networks, CNY has the second ranked influence-strength, which reveals that CNY has a powerful influence in the FX market. This result may be attributed to not only the strong correlation between CNY and USD but also the increasing power and economic status of China. For the rest of the

[3] For the full list of the ranked currencies by the influence-strength, it can be obtained from the authors upon request.

Table 4
The top and the bottom five currencies ranked by the influence-strength (IS) in the lower- and upper-tail dependence MST and PMFG networks.

Rank	Lower-tail MST		Upper-tail MST		Lower-tail PMFG		Upper-tail PMFG	
	Currency	IS	Currency	IS	Currency	IS	Currency	IS
1	USD	5.4840	USD	4.4967	USD	7.9692	USD	6.1590
2	JOD	3.0480	JOD	2.5232	CNY	5.1366	CNY	5.3947
3	HUF	2.5651	MYR	2.4940	TRY	4.8975	AED	4.6790
4	MXN	2.4262	EUR	2.3974	HUF	4.7683	TWD	4.1751
5	EUR	2.2989	MXN	2.2414	SAR	4.7157	PLN	4.1103
38	CAD	0.3666	COP	0.2795	CAD	0.9720	VND	0.8974
39	GBP	0.3147	RUB	0.2481	GBP	0.7714	RUB	0.6524
40	RUB	0.2880	GBP	0.2040	RUB	0.7683	ILS	0.4987
41	ILS	0.2835	ILS	0.1919	ILS	0.7534	GBP	0.4750
42	JPY	0.0391	JPY	0.0637	JPY	0.0486	JPY	0.0638

Notes: Due to space limitations, we omit the “dependence” in the terms of lower- and upper-tail dependence MST and PMFG.

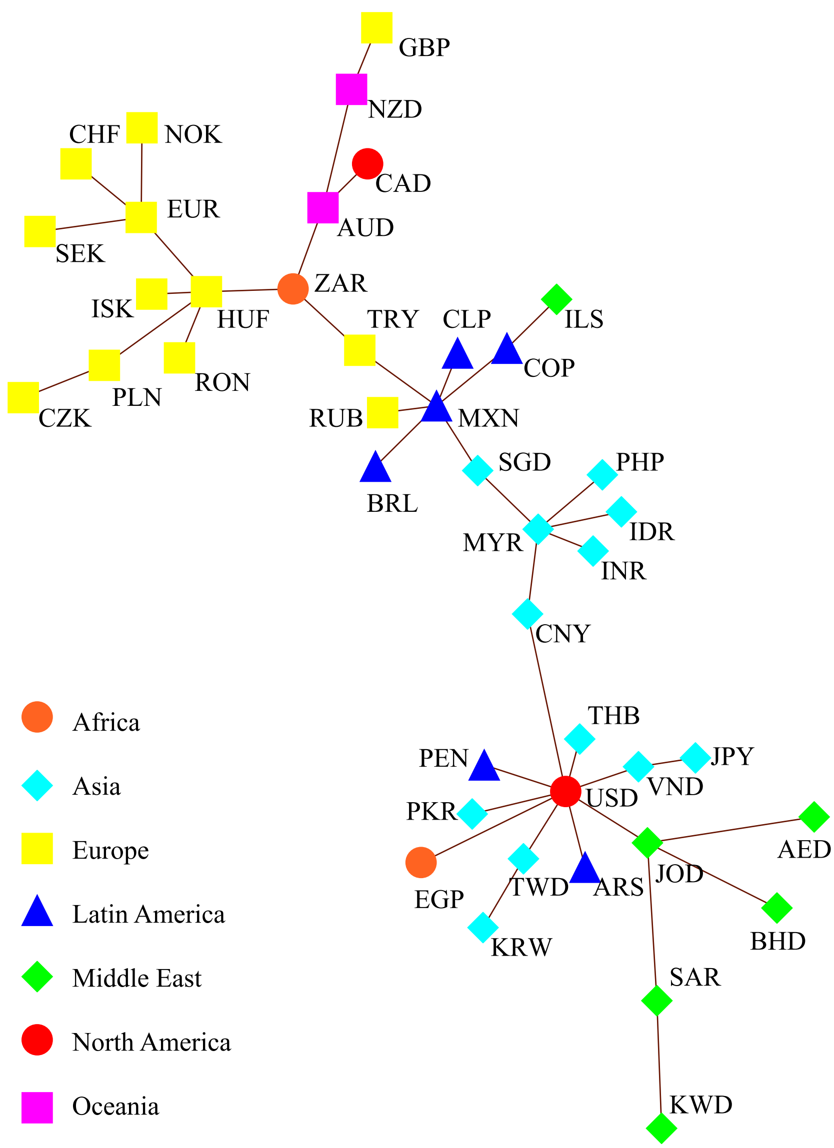

Fig. 3. Lower-tail dependence MST of the set of 42 currencies in the FX market during the period 2005–2012. Currencies from the same geographical location (i.e., continent or region) are marked the same color and shape. Coding is: Africa, orange ellipses; Asia, cyan diamonds; Europe, yellow squares; Latin America, blue triangles; Middle East, green diamonds; North America, red ellipses; and Oceania, magenta squares.(For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

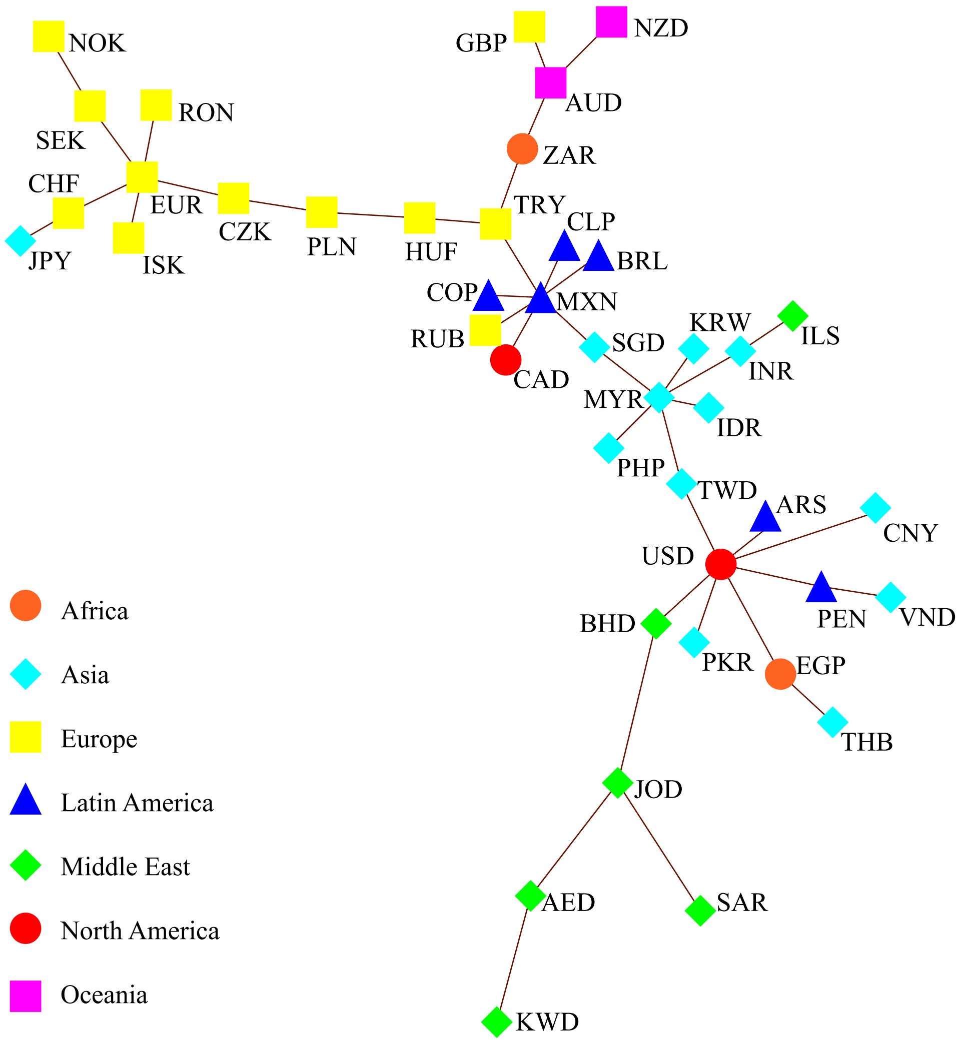

Fig. 4. Upper-tail dependence MST of the set of 42 currencies in the FX market during the period 2005–2012. Currencies from the same geographical location (i.e., continent or region) are marked the same color and shape. Coding is: Africa, orange ellipses; Asia, cyan diamonds; Europe, yellow squares; Latin America, blue triangles; Middle East, green diamonds; North America, red ellipses; and Oceania, magenta squares. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

top five currencies, there are different in different tail dependence networks. As presented in Table 4, the bottom five ranked currencies show two interesting phenomena as follows. (1) Two important currencies GBP and JPY appear as the low influence vertex (asset) in the four tail dependence networks. The following reasons may be accounted for the positions of the two currencies. As for GBP, although Britain is a member of the European Union, its monetary policy and FX regime are independent; while for JPY, the FX regime of Japan, which is a special case in the developed countries, is to keep JPY as a weak currency. (2) Another two currencies RUB and ILS are members of the bottom five currencies ranked by the influence-strength in the four tail dependence networks. The positions of the two currencies in the network are just like their counties' (i.e., Russia and Israel) special political role and geographic location in the world.

3.4. Results of lower- and upper-tail dependence MSTs and HTs

In Figs. 3 and 4, we show the lower- and upper-tail dependence MSTs of the set of 42 currencies in the FX market obtained from the corresponding tail dependence matrices estimated by using 2003 daily returns during the analyzed period (2005–2012), respectively. In each figure, we mark currencies from the same continent or region as the same color and shape.

From Figs. 3 and 4, one can observe that majorities of currencies are clustered together according to their geographical distributions. For instance, the European cluster, Asian cluster, Latin American, Middle Eastern cluster with EUR (HUF), MYR, MXN, and JOD at their centers are formed in the tail dependence MSTs. Besides, it can be found that an important cluster—the international cluster with the USD at its hub—is directly or indirectly linked with currencies from Asia, Middle East, Latin America, and Africa. Another interesting cluster is the Commonwealth cluster that consists of AUD and NZD from Oceania, GBP from Europe, ZAR from Africa, and (or) CAD from North America. The name of the Commonwealth cluster is reported by Wang et al. (2013a, 2014) who consider that countries of the five or four currencies are from the Commonwealth of Nations.

As a whole, the two tail dependence MSTs are similar. But some differences can be found between the two MSTs such as the network's structure and currencies' position. For example, the European cluster in the lower-tail dependence MST is tighter than in the upper-tail dependence MST. Positions of three currencies (JPY, ILS, and CAD), which are ranked in the last five currencies by the influence-strength, are changed. In detail, JPY, ILS, and CAD connected in the international cluster, the Latin American cluster, and the Commonwealth cluster change to link with the European cluster, the Asian cluster, and the

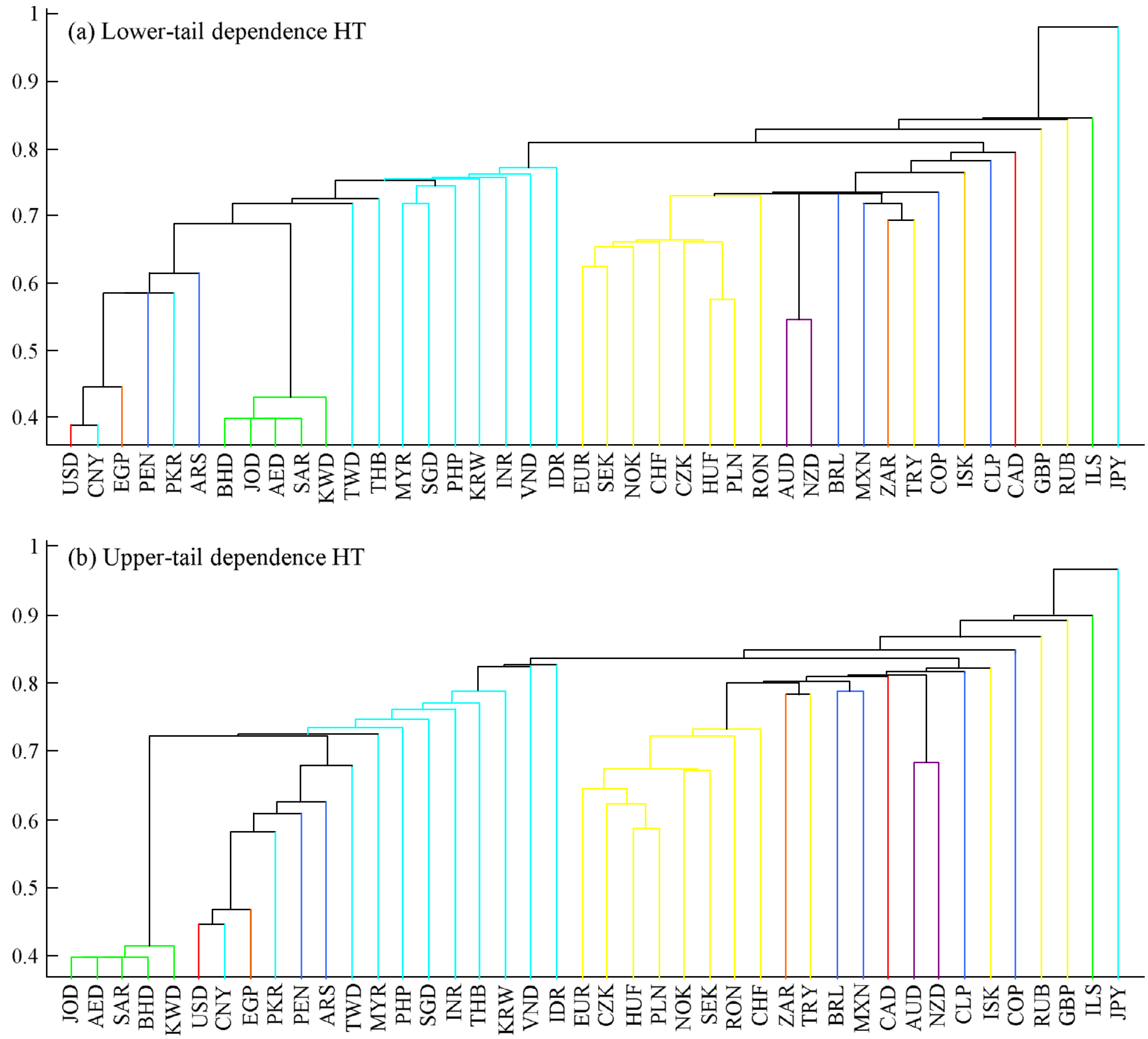

Fig. 5. (a) Lower- and (b) upper-tail dependence HTs of the set of 42 currencies in the FX market during the period 2005–2012. Currencies from the same geographical location (i.e., continent or region) are marked the same color. Coding is: Africa, orange; Asia, cyan; Europe, yellow; Latin America, blue; Middle East, green; North America, red; and Oceania, magenta. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

Latin American cluster, respectively. Therefore, participants in the FX market should take care that the currency clusters change in different tail dependence MSTs, and the special currencies like JPY and ILS with a peripheral position in the network have a low influence-strength.

As usual, in Fig. 5, we draw the lower- and upper-tail dependence hierarchical trees (HTs) associated with the MSTs. Currencies from the same continent or region are marked the same color. In a HT, if a horizontal line is plotted between two (or more) vertical lines, the two (or more) currencies (i.e., vertical lines) are connected or clustered together. From Fig. 5(a), we can find that the distance between USD and CNY is the smallest of the empirical data, suggesting a strong lower-tail dependence between the two currencies that forms a cluster. We call this cluster as the international cluster because it also links other currencies like EGP, PEN, PKR, ARS, the Middle Eastern cluster that is composed of BHD, JOD, AED, SAR, and KWD, etc. Except for CNY, PKR, and JPY, currencies from Asia are linked and lined together to form the Asian cluster. Similar to the Asian cluster, except for TRY, GBP, and RUB, currencies from Europe are connected to form the European cluster that consists of two sub-groups, one with EUR and SEK and the other with HUF and PLN. Besides, AUD and NZD make up the Oceanian cluster in the HT. An inhomogeneous cluster, which consists of ZAR, TRY, and MXN from different continents, are formed in the HT.

From Fig. 5(b), we can see that the whole structure observed in the upper-tail dependence HT is in line with Fig. 5(a), but some related changes can be found as follows. (1) The Middle Eastern cluster becomes the first cluster that has the smallest distance among its currencies. (2) Although Asian currencies are lined together, the centers of cluster (i.e., MYR and SGD) appeared in Fig. 5(a) is gone. (3) The sub-group with EUR and SEK in the European cluster is replaced by the sub-group with NOK and SEK. (4) The South American cluster is formed with BRL and MXN in the upper-tail dependence HT. It is interesting to note that the final four currencies lined in the two tail dependence HTs are RUB, GBP, ILS, and JPY, which is consistent with the results ranked by the influence-strength in Table 4.

3.5. Results of lower- and upper-tail dependence PMFGs

In this subsection, we consider the lower- and upper-tail dependence PMFGs of the set of 42 currencies in the FX market obtained from the corresponding tail dependence matrices estimated by using 2003 daily returns during the analyzed period (2005–2012), and

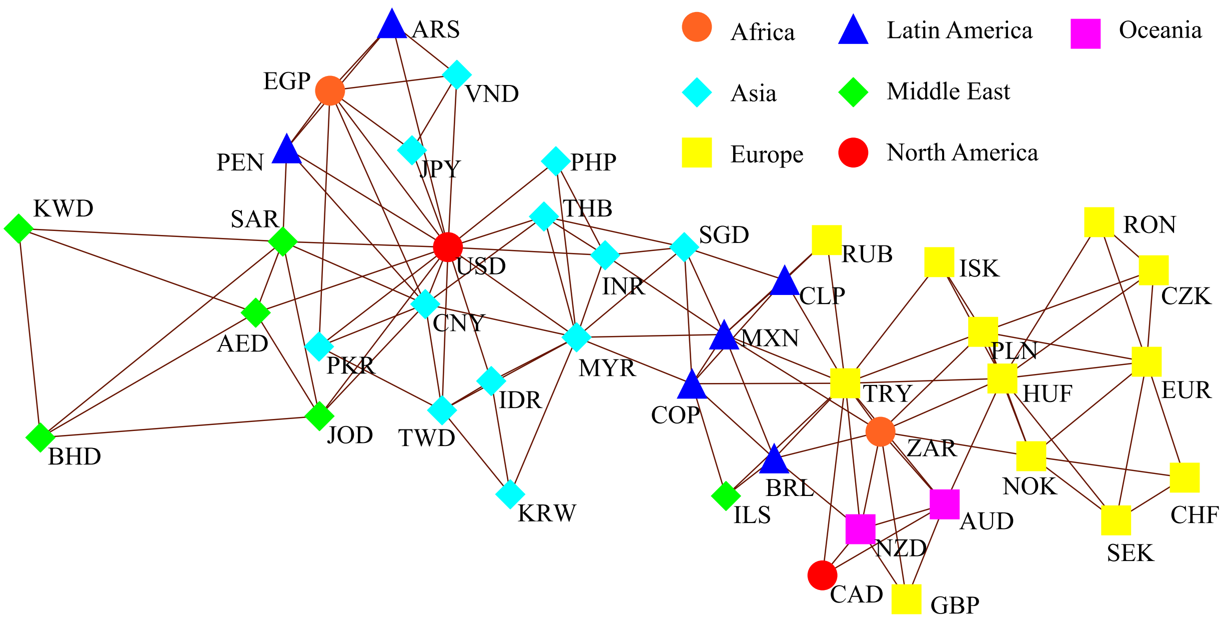

Fig. 6. Lower-tail dependence PMFG of the set of 42 currencies in the FX market during the period 2005–2012. Currencies from the same geographical location (i.e., continent or region) are marked the same the color and shape. Coding is: Africa, orange ellipses; Asia, cyan diamonds; Europe, yellow squares; Latin America, blue triangles; Middle East, green diamonds; North America, red ellipses; and Oceania, magenta squares. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

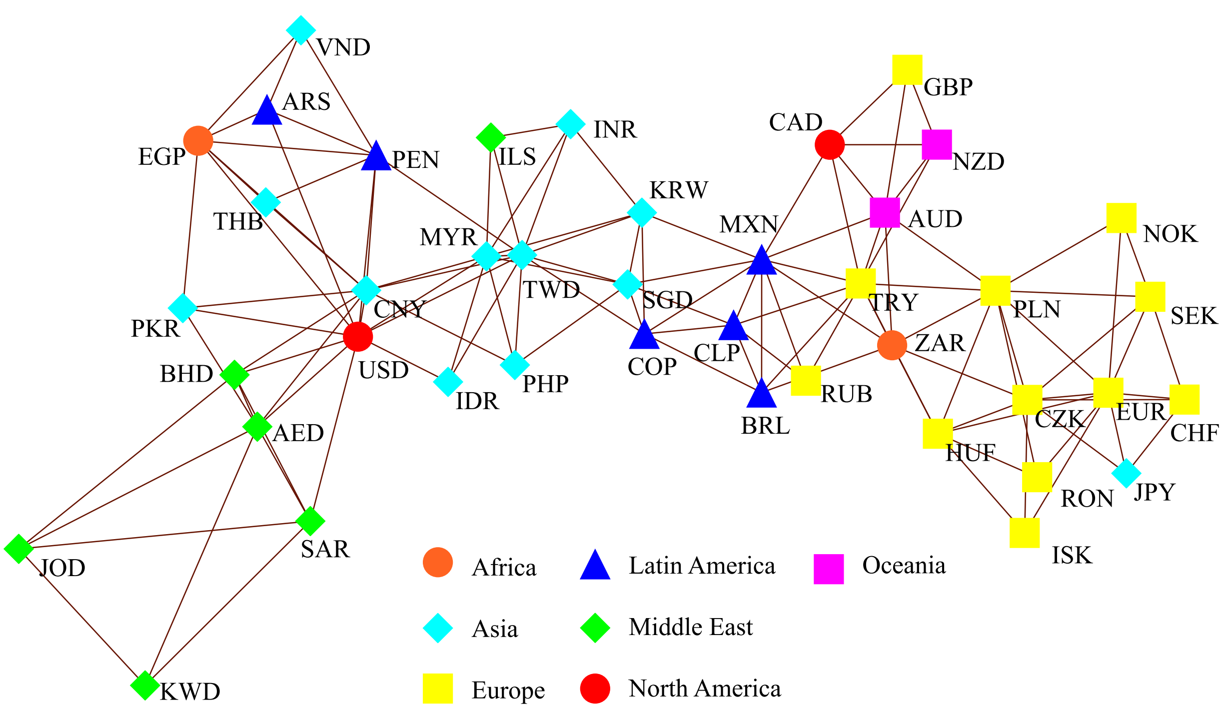

Fig. 7. Upper-tail dependence PMFG of the set of 42 currencies in the FX market during the period 2005–2012. Currencies from the same geographical location (i.e., continent or region) are marked the same the color and shape. Coding is: Africa, orange ellipses; Asia, cyan diamonds; Europe, yellow squares; Latin America, blue triangles; Middle East, green diamonds; North America, red ellipses; and Oceania, magenta squares. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

present the two tail dependence PMFGs in Figs. 6 and 7. Similar to Figs. 3 and 4, currencies from the same geographical location are marked the same color and shape in Figs. 6 and 7.

As the outcomes observed in the two tail dependence MSTs, the tail dependence structure between currencies in the FX market drawn by the tail dependence PMFGs is primarily of geographical origin. Concretely, expect for some currencies from the international cluster and the Commonwealth cluster, most currencies from the same geographical location (i.e., continent or region) in the FX market are grouped to form the geographical clusters. In comparison to the tail dependence MSTs, the tail dependence PMFGs include more edges and thus generate more information. In Section 2.5, we introduce that one of differences between the MST and PMFG is the later contains 3-cliques and 4-cliques. By using the n-clique algorithm proposed by Palla, Derenyi, Farkas, and Vicsek (2005), we calculate that the lower-tail dependence PMFG contains 17 and 12

Table 5
3-cliques ranked by the average tail dependence coefficients ($\langle\tau_{ij}^L\rangle$ or $\langle\tau_{ij}^U\rangle$) of lower- and upper-tail dependence PMFGs of the set of 42 currencies in the FX market.

Lower-tail dependence PMFG				Upper-tail dependence PMFG			
Cy. 1	Cy. 2	Cy. 3	$\langle\tau_{ij}^L\rangle$	Cy. 1	Cy. 2	Cy. 3	$\langle\tau_{ij}^U\rangle$
BHD	JOD	AED	0.8380	USD	SAR	AED	0.5949
USD	PEN	SAR	0.5136	BHD	CNY	AED	0.5870
EUR	NOK	PLN	0.5116	CZK	PHP	SEK	0.5175
CNY	PEN	SAR	0.4877	HUF	PLN	RUB	0.4864
BRL	MXN	TRY	0.4666	EUR	PLN	RON	0.4840
ARS	EGP	VND	0.4607	EGP	PEN	THB	0.4410
MXN	ZAR	TRY	0.4590	CNY	PEN	THB	0.4307
CZK	HUF	RON	0.4575	MYR	PHP	SGD	0.3992
COP	MXN	TRY	0.4400	PHP	SGD	TWD	0.3520
HUF	NOK	ZAR	0.4158	CHF	CZK	SEK	0.3347
NOK	PLN	ZAR	0.4008	CAD	MXN	TRY	0.3222
CHF	NOK	SEK	0.3991	GBP	AUD	NZD	0.3099
AUD	HUF	AED	0.3921	BRL	COP	MXN	0.3032
ISK	PLN	TRY	0.3688	AUD	MXN	TRY	0.2909
CLP	MXN	SGD	0.3367	MXN	SGD	KRW	0.2874
INR	MXN	SGD	0.3317	CLP	MXN	SGD	0.2747
JPY	EGP	VND	0.1518	ILS	MYR	TWD	0.2603
				INR	ILS	TWD	0.2331
				COP	MXN	KRW	0.2275
				JPY	CHF	CZK	0.1169

Notes: The abbreviation "Cy." stands for "Currency".

Table 6
4-cliques ranked by the average tail dependence coefficients ($\langle\tau_{ij}^L\rangle$ or $\langle\tau_{ij}^U\rangle$) of lower- and upper-tail dependence PMFGs of the set of 42 currencies in the FX market.

Lower-tail dependence PMFG					Upper-tail dependence PMFG				
Cy. 1	Cy. 2	Cy. 3	Cy. 4	$\langle\tau_{ij}^L\rangle$	Cy. 1	Cy. 2	Cy. 3	Cy. 4	$\langle\tau_{ij}^U\rangle$
BHD	KWD	SAR	AED	0.8247	BHD	JOD	SAR	AED	0.8388
USD	JOD	SAR	AED	0.6810	JOD	KWD	SAR	AED	0.8297
EUR	HUF	NOK	SEK	0.5278	EUR	NOK	PLN	SEK	0.5056
AUD	NZD	ZAR	TRY	0.4856	CZK	HUF	PLN	ZAR	0.4605
HUF	PLN	ZAR	TRY	0.4703	CNY	MYR	PHP	TWD	0.4418
BRL	NZD	ZAR	TRY	0.4173	ARS	EGP	PEN	VND	0.4362
CAD	AUD	NZD	TRY	0.4119	HUF	PLN	ZAR	TRY	0.4013
INR	MYR	SGD	THB	0.4071	MYR	SGD	KRW	TWD	0.3983
GBP	AUD	NZD	ZAR	0.3950	USD	IDR	MYR	TWD	0.3917
IDR	MYR	KRW	TWD	0.3685	INR	MYR	KRW	TWD	0.3881
COP	MYR	MXN	SGD	0.3522	BRL	MXN	ZAR	TRY	0.3391
CLP	MXN	RUB	TRY	0.3309	AUD	PLN	ZAR	TRY	0.3289
					CAD	AUD	NZD	TRY	0.3235
					COP	SGD	KRW	TWD	0.2905
					CLP	MXN	RUB	TRY	0.2581

Notes: The abbreviation "Cy." stands for "Currency".

3-cliques and 4-cliques, respectively. While in the upper-tail dependence PMFG, we count that the number of 3-cliques and 4-cliques are 20 and 15 respectively. The number of 3-cliques or 4-cliques of the two tail dependence PMFGs is far smaller than the number of possible cliques of three or four elements in a fully linked graph, which is $C_{42}^3 = 11,480$ or $C_{42}^4 = 111,930$. The complete lists of 3-cliques and 4-cliques showed in the two tail dependence PMFSs are described in Tables 5 and 6, respectively. The lists in Tables 5 and 6 are ranked by the average tail dependence coefficients of three or four elements. From Table 5, one can find that the 3-cliques between the lower- and upper-tail dependence PMFGs is almost completely different, except for one case, namely the 3-cliques with elements of CLP, MXN and SGD. As for the 4-cliques in Table 6, most of them are different between the two PMFGs, except for three cases, i.e., 4-cliques with elements of HUF, PLN, ZAR and TRY, CAD, AUD, NZD and TRY, and CLP, MXN, RUB and TRY. Therefore, market participants should pay attention to differences of the 3-cliques and 4-cliques between the two tail dependence PMFGs, and immediately adjust the decision-makings once the market situation changes. Besides, one can see that most of elements of 3-cliques and 4-cliques are from the same currency cluster observed in the tail dependence MSTs or HTs. From this, portfolio holders should choose currencies (assets) from different 3-cliques and 4-cliques or clusters to build the portfolios, which is helpful for investment diversifications and reducing the risk of portfolios.

The community structure is another important topological feature in the complex network, which represents the emergence of clusters of vertexes in a complex network that are more compactly linked internally than the rest of the complex network. In the existing literature on financial networks, the community structure is widely found and reported in the PMFG network. For instance, Song, Tumminello, Zhou, and Mantegna (2011) investigate the PMFG network of the set of 57 market indices from 1 January 1996 to 31 July 2009 and detect four communities in the PMFG. Similar to Song et al. (2011), four communities are detected in the PMFG of industrial indices of U.S. equity markets by Buccheri et al. (2013) who examine the 49 industry index time series during the period 1969–2011. Wang and Xie (2015) uncover three communities in the PMFG network of 20 national real estate securities markets in the period 2006–2012. In previous works, scholars develop many useful methods to detect the community structure in the complex networks

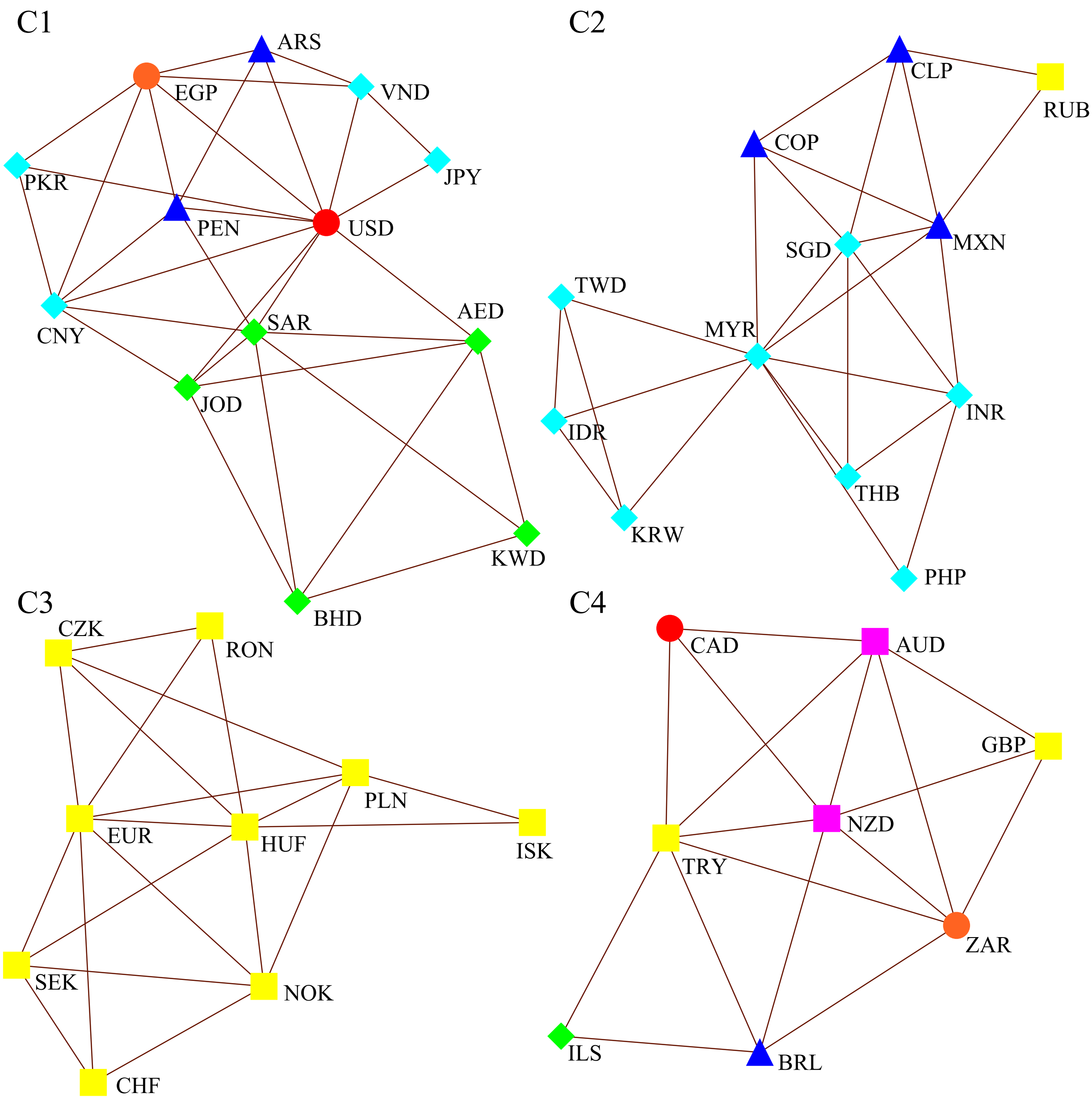

Fig. 8. Four communities detected into the lower-tail dependence PMFG (computed by using the daily returns of 42 currencies in the FX market during the period 2005–2012) by the Louvain approach (Blondel et al., 2008). Currencies from the same geographical location (i.e., continent or region) are marked the same color and shape. Coding is: Africa, orange ellipses; Asia, cyan diamonds; Europe, yellow squares; Latin America, blue triangles; Middle East, green diamonds; North America, red ellipses; and Oceania, magenta squares. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

(see, e.g., Blondel, Guillaume, Lambiotte, & Lefebvre, 2008; Fortunato, 2010; Palla et al., 2005). To identify the community structure in the tail dependence PMFGs, we employ a simple, efficient and easy-to-implement detecting tool proposed by Blondel et al. (2008), which is called as the Louvain approach.[4]

In Figs. 8 and 9, we present the communities of the lower- and upper-tail dependence PMFGs respectively. Like in Song et al. (2011) and Buccheri et al. (2013), four communities are identified in each tail dependence PMFG. From Fig. 8, one can see that the four detected communities correspond primarily to different clusters observed in the tail dependence MSTs: top left, the international cluster and the Middle Eastern cluster; top right, the Asian cluster and Latin American cluster; bottom left, the European cluster; and bottom right, the Commonwealth cluster. We denote the four communities as C1, C2, C3, and C4 from top left to bottom right. Compared with the four detected communities in Fig. 8, we can find some changes in the upper-tail dependence PMFG in Fig. 9 as follows. (1) The community C1 has a small change, namely THB joins the community instead of JPY. (2) The community C2 reduces to the Asian cluster, and the ILS from the (lower-tail) community C4 adds in this community. (3) The community structure of C3 is restructured and consists of most European currencies and JPY. (4) The Latin American cluster and the Commonwealth cluster are merged to form the new community C4. By comparing communities with 3-cliques and 4-cliques, one can see that the size of community is larger than the 3-cliques and 4-cliques, and some 3-cliques and 4-cliques are covered in the same community. Therefore, when portfolio holders choose the suitable currencies in the portfolios, they should not only consider 3-cliques and

[4] The cause of such a name of the Louvain approach is that the method was developed when the authors in Blondel et al. (2008) all were at the Université catholique de Louvain.

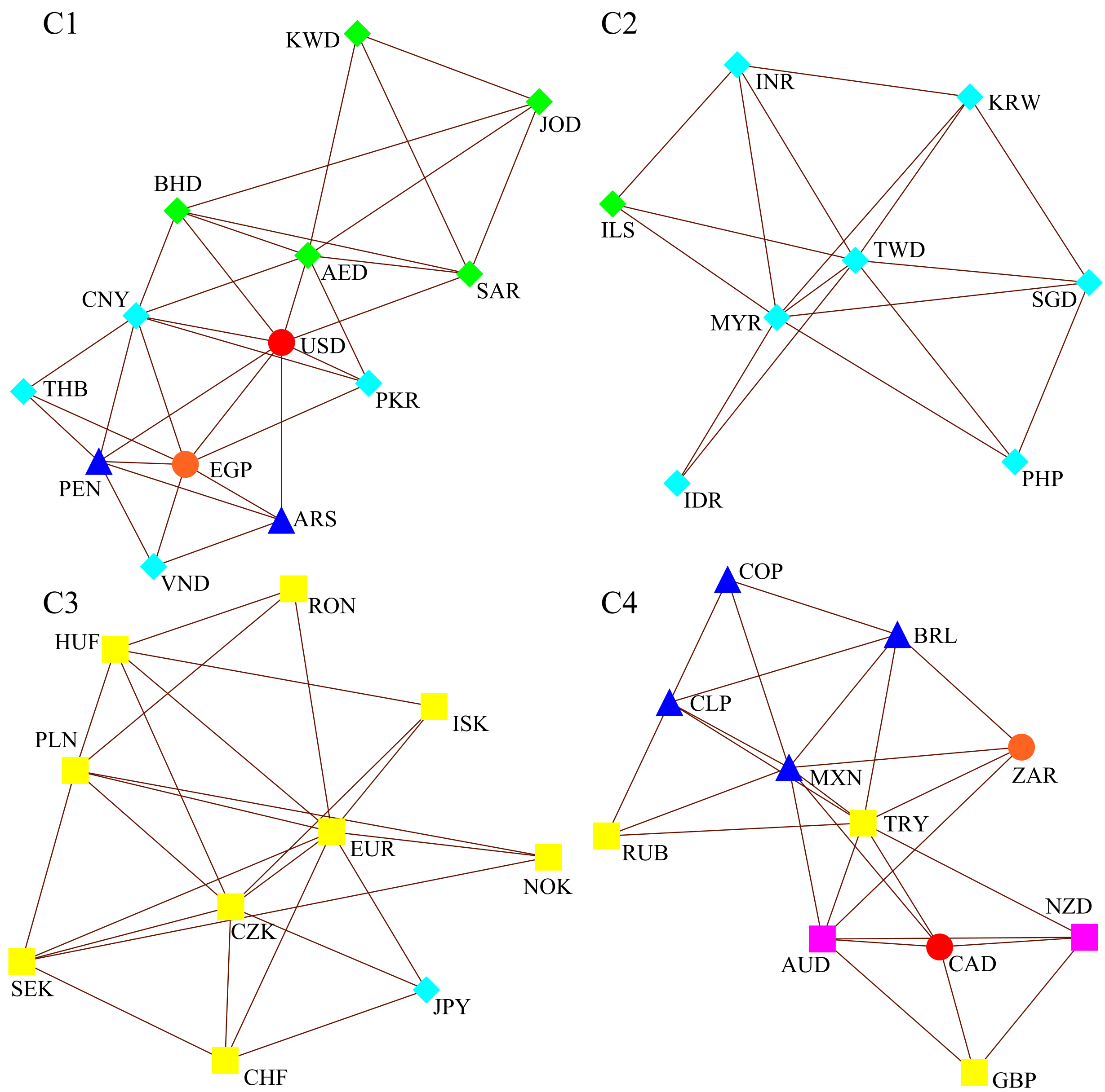

Fig. 9. Four communities detected into the upper-tail dependence PMFG (computed by using the daily returns of 42 currencies in the FX market during the period 2005–2012) by the Louvain approach (Blondel et al., 2008). Currencies from the same geographical location (i.e., continent or region) are marked the same color and shape. Coding is: Africa, orange ellipses; Asia, cyan diamonds; Europe, yellow squares; Latin America, blue triangles; Middle East, green diamonds; North America, red ellipses; and Oceania, magenta squares. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article).

4-cliques, but also take into account the community structure that is different during different market situations (e.g., a booming market or a recession market).

4. Conclusions and future works

In this paper, we examine the tail dependence structure of a set of 42 currencies in the FX market in the range from the beginning of 2005 to the end of 2012. Based on the SJC copula model and the MST and PMFG approaches, we construct lower- and upper-tail dependence networks to analyze the tail dependence structure of the FX market. In practice, we first employ the AR(1)-GARCH(1,1)-*t* model to characterize marginal distributions of FX rates returns. Then, we adopt the SJC copula model to compute the lower- and upper-tail dependence coefficients between each pair of FX rates. Next, we build the lower- and upper-tail dependence matrices and transform the two tail dependence matrices to two distance matrices. Finally, we use the MST and PMFG method to construct the tail dependence networks and study their topological properties, the cluster and community structure. Meanwhile, we also investigate the lower- and upper-tail dependence HTs associated with the MSTs. Some basic findings for investigating tail dependence structure of the FX market are summarized as follows.

(1) By analyzing the statistics of lower- and upper-tail dependence coefficients, we find that the two series of tail dependence coefficients present different distributions.

(2) Based on the analysis of topological properties of the tail dependence networks, we come to conclusions that the two PMFG networks are small-world networks, the upper-tail dependence networks are tighter than the lower-tail dependence networks, and the influence-strength distributions of four tail dependence networks follow a power-law.

(3) Some clusters are observed in the tail dependence MSTs and HTs, such as the international cluster, the European cluster, the Asian cluster, the Middle Eastern cluster, the Latin American cluster, and the Commonwealth cluster with USD, EUR, MYR, JOD, MXN, and AUD at their centers, and most clusters are formed according to their currencies' geographical origin. Currencies like JPY, GBP, ILS, and RUB with a peripheral position in the MST networks have a weak influence-strength.

(4) 3-cliques and 4-cliques are found in the lower- and upper-tail dependence PMFGs, and the number of cliques with three and four elements of the latter is more than that of the former. Four communities are respectively detected in the two tail dependence PMFGs, and some differences of the four identified communities between the two tail dependence PMFGs are found.

As a whole, the tail dependence structure between the lower- and upper-tail dependence networks (i.e., MSTs, HTs, and PMFGs) is similar, but remarked and subtle differences are coexistence. Therefore, market participants should pay attention to the differences between the two tail dependence networks and be ready to adjust the decision-makings once the market status is varying from a depression period to a booming period and vice versa.

One of the notable contributions of this paper is that we propose the concept of lower- and upper-tail dependence networks, which combines the SJC copula model with the traditional dependence network methods (i.e., the MST and PMFG). The tail dependence networks can provide a new angle of view for analyzing the dependence structure of financial markets, and a novel tool for market participants. In practical terms, our contributions to the field of expert and intelligent systems are three-fold as follows.

(1) The tail dependence networks can be integrated into the foreign exchange trading systems. Analyzing the links and clusters of the tail dependence networks in the FX trading systems is helpful in the construction of FX portfolio and also important in predicting foreign exchange rates and economic decision-making. On another note, our proposed tail dependence network tool is a methodological contribution to the modern portfolio theory.

(2) In the industry, the financial network methods have been designed to relevant expert and intelligent platforms for visual decision-making in financial management. For instance, one of the famous platforms is the Financial Network Analytics (FNA) platform that maps complex financial systems allowing its users to make better data-driven decisions (Birch et al., 2015). Therefore, our proposed tail dependence networks also can be applied and designed to a similar decision-making platform.

(3) From a macro-perspective, by identifying the changes and differences of links, clusters and communities in the lower- and upper-tail dependence networks, we can design and construct an early warning system (EWS) to forecast the extreme events and estimate relevant tail risks in the FX market.

Despite the significant contributions of our proposed tail dependence networks to the fields of expert and intelligent systems and financial management, some open topics are not examined in this study but can be extended for the future works as follows.

(1) As noted, a useful application of the tail dependence networks is in the portfolio management. When we construct an asset portfolio, the key problem is how to select the assets in the optional basket based on the tail dependence networks. Therefore, it is urgent to design an intelligent selecting algorithm to achieve the optimal portfolio according to the topological features of the tail dependence networks.

(2) One of the major limitations in our work is that the dynamic properties of the FX market are not considered. It is well-known that financial markets are complex dynamic systems, so the tail dependence structure between financial agents is time-varying. Thus, another interesting future work is to investigate dynamics of the tail dependence networks, which can be conducive to understand the dynamic mechanism of financial markets from a new perspective and construct visual and self-adapting decision-making system in financial management.

(3) In recent years, many factors such as the frequent bursting of financial crises, rapid shock of oil prices, wild speculation of investors, and unstable political situation of several countries lead to the dramatic fluctuation of the asset prices and then the instability of financial markets. The study of the stability of financial markets becomes a hot topic both in academic and industrial fields. So it would be an insight future research on the stability of financial markets by examining the stability of dynamic tail dependence networks and building relevant early warning systems.

(4) Another potential and insight future study is to construct a crisis simulation model of tail dependence networks for financial markets. According to topological properties (e.g., the degree distribution, average path length, average clustering coefficient, clusters, and community structure) of empirical financial networks, this crisis simulation model can be used to generate simulated tail dependence networks for predicting extreme events and crises.

Acknowledgments

We are grateful to the main editor and two anonymous referees for their helpful suggestions that significantly improved the quality of the paper. The research is supported by the National Natural Science Foundation of China (Grant nos. 71501066 and 71373072), the China Scholarship Council (Grant no. 201506135022), the Specialized Research Fund for the Doctoral Program of Higher Education (Grant no. 20130161110031), and the Foundation for Innovative Research Groups of the National Natural Science Foundation of China (Grant no. 71221001).

References

Aloui, R., Ben Aïssa, M. S., & Nguyen, D. K. (2013). Conditional dependence structure between oil prices and exchange rates: a copula-GARCH approach. *Journal of International Money and Finance, 32*, 719–738.

Aste, T., Shaw, W., & Di Matteo, T. (2010). Correlation structure and dynamics in volatile markets. *New Journal of Physics, 12*(8), 085009.

Bae, K. H. (2003). A new approach to measuring financial contagion. *Review of Financial Studies, 16*(3), 717–763.

Basher, S. A., Nechi, S., & Zhu, H. (2014). Dependence patterns across Gulf Arab stock markets: a copula approach. *Journal of Multinational Financial Management, 25–26*, 30–50.

Birch, J., Pantelous, A. A., & Soramäki, K. (2015). Analysis of correlation based networks representing DAX 30 stock price returns. *Computational Economics*. doi:10.1007/s10614-015-9481-z.

Blondel, V. D., Guillaume, J.-L., Lambiotte, R., & Lefebvre, E. (2008). Fast unfolding of communities in large networks. *Journal of Statistical Mechanics: Theory and Experiment, 2008*(10), P10008.

Boginski, V., Butenko, S., & Pardalos, P. M. (2005). Statistical analysis of financial networks. *Computational Statistics & Data Analysis, 48*(2), 431–443.

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. *The Review of Economics and Statistics, 69*(3), 542–547.

Brida, J. G., Gómez, D. M., & Risso, W. A. (2009). Symbolic hierarchical analysis in currency markets: an application to contagion in currency crises. *Expert Systems with Applications, 36*(4), 7721–7728.

Brida, J. G., & Risso, W. A. (2010). Hierarchical structure of the German stock market. *Expert Systems with Applications, 37*(5), 3846–3852.

Brooks, C. (2008). *Introductory econometrics for finance* (2nd). New York: Cambridge University Press.

Buccheri, G., Marmi, S., & Mantegna, R. N. (2013). Evolution of correlation structure of industrial indices of U.S. equity markets. *Physical Review E, 88*(1), 012806.

Clauset, A., Shalizi, C. R., & Newman, M. E. J. (2009). Power-law distributions in empirical data. *SIAM Review, 51*(4), 661–703.

Dias, A., & Embrechts, P. (2010). Modeling exchange rate dependence dynamics at different time horizons. *Journal of International Money and Finance, 29*(8), 1687–1705.

Durante, F., Foscolo, E., Jaworski, P., & Wang, H. (2014). A spatial contagion measure for financial time series. *Expert Systems with Applications, 41*(8), 4023–4034.

Fenn, D. J., Porter, M. A., Mucha, P. J., McDonald, M., Williams, S., Johnson, N. F., & Jones, N. S. (2012). Dynamical clustering of exchange rates. *Quantitative Finance, 12*(10), 1493–1520.

Fortunato, S. (2010). Community detection in graphs. *Physics Reports, 486*(3–5), 75–174.

Frankel, J. A., & Xie, D. (2010). Estimation of de facto flexibility parameter and basket weights in evolving exchange rate regimes. *American Economic Review, 100*(2), 568–572.

Hammoudeh, S., Mensi, W., Reboredo, J. C., & Nguyen, D. K. (2014). Dynamic dependence of the global Islamic equity index with global conventional equity market indices and risk factors. *Pacific-Basin Finance Journal, 30*, 189–206.
Hoesli, M., & Reka, K. (2015). Contagion channels between real estate and financial markets. *Real Estate Economics, 43*(1), 101–138.
Hu, J. (2010). Dependence structures in Chinese and US financial markets: a time-varying conditional copula approach. *Applied Financial Economics, 20*(7), 561–583.
Huang, M., & Wu, C. (2015). Economic benefits and determinants of extreme dependences between REIT and stock returns. *Review of Quantitative Finance and Accounting, 44*(2), 299–327.
Jammazi, R., Tiwari, A. K., Ferrer, R., & Moya, P. (2015). Time-varying dependence between stock and government bond returns: international evidence with dynamic copulas. *The North American Journal of Economics and Finance, 33*, 74–93.
Jang, W., Lee, J., & Chang, W. (2011). Currency crises and the evolution of foreign exchange market: Evidence from minimum spanning tree. *Physica A, 390*(4), 707–718.
Ji, Q., & Fan, Y. (2014). Evolution of the world crude oil market integration: a graph theory analysis. *Energy Economics*. doi:10.1016/j.eneco.2014.12.003.
Joe, H. (1997). *Multivariate models and dependence concepts*. London: Chapman & Hall.
Joe, H., & Xu, J. J. (1996). *The estimation method of inference functions for margins for multivariate models*. Vancouver, Canada: Department of Statistics, University of British Columbia Technical report 166.
Keskin, M., Deviren, B., & Kocakaplan, Y. (2011). Topology of the correlation networks among major currencies using hierarchical structure methods. *Physica A, 390*(4), 719–730.
Kim, H.-J., Lee, Y., Kahng, B., & Kim, I.-m. (2002). Weighted scale-free network in financial correlations. *Journal of the Physical Society of Japan, 71*(9), 2133–2136.
Kruskal, J. B., Jr. (1956). On the shortest spanning subtree of a graph and the traveling salesman problem. *Proceedings of the American Mathematical Society, 7*(1), 48–50.
Kwapień, J., & Drożdż, S. (2012). Physical approach to complex systems. *Physics Reports, 515*(3–4), 115–226.
Kwapień, J., Gworek, S., & Drożdż, S. (2009). Structure and evolution of the foreign exchange networks. *Acta Physica Polonica B, 40*(1), 175–194.
Lai, Y. H., Chen, C. W. S., & Gerlach, R. (2009). Optimal dynamic hedging via copula-threshold-GARCH models. *Mathematics and Computers in Simulation, 79*(8), 2609–2624.
Mai, Y., Chen, H., & Meng, L. (2014). An analysis of the sectorial influence of CSI300 stocks within the directed network. *Physica A, 396*, 235–241.
Mantegna, R. N. (1999). Hierarchical structure in financial markets. *The European Physical Journal B, 11*(1), 193–197.
Matesanz, D., & Ortega, G. J. (2014). Network analysis of exchange data: Interdependence drives crisis contagion. *Quality & Quantity, 48*(4), 1835–1851.
Matesanz, D., Torgler, B., Dabat, G., & Ortega, G. J. (2014). Co-movements in commodity prices: a note based on network analysis. *Agricultural Economics, 45*(S1), 13–21.
Nelsen, R. B. (2006). *An introduction to copulas* (2nd). New York: Springer.
Ning, C. (2010). Dependence structure between the equity market and the foreign exchange market—a copula approach. *Journal of International Money and Finance, 29*(5), 743–759.
Ning, C., Xu, D., & Wirjanto, T. S. (2015). Is volatility clustering of asset returns asymmetric? *Journal of Banking & Finance, 52*, 62–76.
Onnela, J. P., Chakraborti, A., Kaski, K., Kertesz, J., & Kanto, A. (2003). Dynamics of market correlations: taxonomy and portfolio analysis. *Physical Review E, 68*(5), 056110.
Onnela, J. P., Kaski, K., & Kertész, J. (2004). Clustering and information in correlation based financial networks. *The European Physical Journal B, 38*(2), 353–362.
Palla, G., Derenyi, I., Farkas, I., & Vicsek, T. (2005). Uncovering the overlapping community structure of complex networks in nature and society. *Nature, 435*(7043), 814–818.
Patton, A. J. (2006). Modelling asymmetric exchange rate dependence. *International Economic Review, 47*(2), 527–556.
Podobnik, B., Wang, D., Horvatic, D., Grosse, I., & Stanley, H. E. (2010). Time-lag cross-correlations in collective phenomena. *Europhysics Letters, 90*(6), 68001.
Rachev, S. T., Fabozzi, F. J., & Menn, C. (2005). *Fat-tailed and skewed asset return distributions: implications for risk management, portfolio selection, and option pricing*. New Jersey: John Wiley & Sons.
Sklar, A. (1959). *Fonctions de répartition á n dimensions et leurs marges: 8* (pp. 229–231). Publications de l'Institut de Statistique de l'Université de Paris.
Song, D. M., Tumminello, M., Zhou, W. X., & Mantegna, R. N. (2011). Evolution of worldwide stock markets, correlation structure, and correlation-based graphs. *Physical Review E, 84*(2), 026108.
Sun, C. (2013). On the market risk of securitized timberlands. *Journal of Forest Economics, 19*(2), 110–127.
Tumminello, M., Aste, T., Di Matteo, T., & Mantegna, R. N. (2005). A tool for filtering information in complex systems. *Proceedings of the National Academy of Sciences of the United States of America, 102*(30), 10421–10426.
Tumminello, M., Lillo, F., & Mantegna, R. N. (2010). Correlation, hierarchies, and networks in financial markets. *Journal of Economic Behavior & Organization, 75*(1), 40–58.
Wang, G.-J., & Xie, C. (2013). Cross-correlations between Renminbi and four major currencies in the Renminbi currency basket. *Physica A, 392*(6), 1418–1428.
Wang, G.-J., & Xie, C. (2015). Correlation structure and dynamics of international real estate securities markets: a network perspective. *Physica A, 424*, 176–193.
Wang, G.-J., Xie, C., Chen, S., Yang, J.-J., & Yang, M.-Y. (2013b). Random matrix theory analysis of cross-correlations in the US stock market: evidence from pearson's correlation coefficient and detrended cross-correlation coefficient. *Physica A, 392*(17), 3715–3730.
Wang, G.-J., Xie, C., Chen, Y.-J., & Chen, S. (2013a). Statistical properties of the foreign exchange network at different time scales: evidence from detrended cross-correlation coefficient and minimum spanning tree. *Entropy, 15*(5), 1643–1662.
Wang, G.-J., Xie, C., Han, F., & Sun, B. (2012). Similarity measure and topology evolution of foreign exchange markets using dynamic time warping method: evidence from minimal spanning tree. *Physica A, 391*(16), 4136–4146.
Wang, G.-J., Xie, C., Zhang, P., Han, F., & Chen, S. (2014). Dynamics of foreign exchange networks: a time-varying copula approach. *Discrete Dynamics in Nature and Society, 2014*, 170921.
Wang, K., Chen, Y.-H., & Huang, S.-W. (2011). The dynamic dependence between the Chinese market and other international stock markets: a time-varying copula approach. *International Review of Economics & Finance, 20*(4), 654–664.
Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of 'small-world' networks. *Nature, 393*(6684), 440–442.
Yan, X.-G., Xie, C., & Wang, G.-J. (2015). Stock market network's topological stability: evidence from planar maximally filtered graph and minimal spanning tree. *International Journal of Modern Physics B, 29*(22), 1550161.
Yang, L., & Hamori, S. (2014a). Gold prices and exchange rates: a time-varying copula analysis. *Applied Financial Economics, 24*(1), 41–50.
Yang, L., & Hamori, S. (2014b). Dependence structure between CEEC-3 and German government securities markets. *Journal of International Financial Markets, Institutions and Money, 29*, 109–125.
Zebende, G. F. (2011). DCCA cross-correlation coefficient: quantifying level of cross-correlation. *Physica A, 390*(4), 614–618.
Zhou, J., & Gao, Y. (2012). Tail dependence in international real estate securities markets. *The Journal of Real Estate Finance and Economics, 45*(1), 128–151.