Dynamic connectedness of global currencies: a conditional Granger-causality approach

Tan Le, Franck Martin, Duc Nguyen

Centre de Recherche en Économie et Management
Center for Research in Economics and Management

University of Rennes 1

University of Caen Normandie

Working Paper

Dynamic connectedness of global currencies: a conditional Granger-causality approach

Tan T. M. Le

Univ Rennes, CREM, CNRS, UMR 6211, F-35000 Rennes, France, and Hue University, Vietnam

Franck Martin

Univ Rennes, CREM, CNRS, UMR 6211, F-35000 Rennes, France

Duc K. Nguyen

Ipag Business School, Paris, France

April 2018 - WP 2018-04

Dynamic connectedness of global currencies: a conditional Granger-causality approach ☆

Tan T.M. Le[a,b], Franck Martin[a], Duc K. Nguyen[c]

[a] *Faculty of Economics, University of Rennes 1, Rennes, FRANCE*
[b] *Hue College of Economics - Hue University, Hue, VIETNAM*
[c] *Ipag Business School, Paris, FRANCE*

Abstract

Conditional granger causality framework in Barnett and Seth (2014) is employed to measure the connectedness among the most globally traded currencies. The connectedness exhibits dynamics through time on both breadth and depth dimensions at three levels: node-wise, group-wise and system-wise. Overall, rolling connectedness series could capture major systemic events like Lehman Brothers' collapse and the get-through of Outright Monetary Transactions in Europe in September 2012. The rolling total breath connectedness series spike during high-risk episodes, becomes more stable in lower risk environment and is positively correlated with volatility index and Ted spread, thus, can be considered as a systemic risk indicator in light of Billio et al. (2012). Global currencies tend structure into communities based on connection strength and density. While more links are found related to currencies from emerging markets, G11 currencies are net spreaders of foreign exchange rate returns. Finally, hard currencies including Canadian dollar, Norwegian Krone and Japanese Yen frequently present among the top most connected, though the centrality positions vary over time.

Keywords: conditional granger causality, exchange rates, connectedness, systemic risk

1. Introduction

Recent global financial crisis 2007 - 2009 has drawn great attention to connectedness within the financial system, reminding that financial connectedness is of critical importance to macroeconomic stability, yet still poorly defined, measured and thus poorly comprehended (Glasserman and Young, 2016; Diebold and Yilmaz, 2015). This *status quo* partly originates from the multi-dimensionality of the concept 'connectedness' itself. Connectedness can be pairwise or system-wide, can focus on institutions, assets or markets, can be directional or non-directional, weighted or non-weighted, static or dynamic, contemporary or lead - lag relationship. As put forward by (Diebold and Yilmaz, 2015), connectedness is closely related to various types of risks, has both desirable and non-desirable parts, but

☆This working paper benefits from Chaire Fondation Rennes 1 "Nouveaux dfis de la banque".
Email address: minhtan@hce.edu.vn (Tan T.M. Le)

is not equivalent to risk. As thus, a good understanding of financial connectedness is beneficial for policy makers in identifying, measuring and managing systemic risk, for investors and portfolio managers in conducting core financial activities like asset pricing, asset allocation and risk management. The connected objects are often, but not limited to, returns and volatility among different assets, asset classes or portfolios.

Foreign exchange market is an inseparable component of modern financial system, acting simultaneously as a facilitator to cross-border activities and as an investment channel. The role of foreign exchange market is reflected through the tremendous trading scale of this global market, which amounted to $5.09 trillion per day in April 2016 (BIS, 2016). Movements in values of key currencies are of interest not only to companies, investors but also to policy makers since they not only affect a country's competitive advantage, its current account and the balance of payment but also lead to foreign exchange rate risks for investors and businesses (Eun and Resnick, 1988; Diebold and Yilmaz, 2015). Besides, several studies document inherent relationships between foreign exchange markets and other financial markets (Menkhoff et al., 2012; Melvin and Taylor, 2009; Apostolakis and Papadopoulos, 2015). Accordingly, foreign exchange markets transmit risks to and receive risks from stock markets, and to some extent, amplify turmoil in stock markets to a global scale . As a result, studying connectedness among global currencies in different periods of time thus also facilitates understanding the dynamic relationship between foreign exchange markets and markets like stocks and bonds.

This study is related to several strands of literature. The first is financial connectedness. Interests in understanding financial connectedness arise with the pulse to identify channels of contagion and to quantify systemic risks. Allen and Gale (2000) see connectedness among financial firms as the cross-holdings of deposits in the interbank market. Based on equilibrium analysis, they come to a conclusion that the density of connectedness strongly affects the possibility of financial contagion. Accordingly, a complete structure - occurs when any bank can hold deposits from others - can produce no contagion from a given shock. In the book 'Connectedness and Contagion - Protecting the financial system from panics', Scott (2016) argues that 'connectedness' is one among the three Cs of systemic risk: Connectedness, Contagion and Correlation. According to the author, 'connectedness occurs when financial institutions are directly overexposed to one another and the failure of one institution would therefore directly bankrupt other institutions, resulting in a chain reaction of failures' (Scott, 2016). Connectedness involves common sharing of resources, on either asset or liability side of the institutions' balance sheets. Analytically, this author focuses on financial institutions, emphasizing the direct over-exposure to each other's assets and liabilities and domino effect of a particular failure as a consequence. Correlation also leads to failure of multiple institutions but, on the other hand, results from collapse of asset prices or exogenous events or herding instinct of asset managers. In other words, according to the author, correlation is 'indirect connectedness'. Billio et al. (2012) assert that connectedness is indeed the 'Linkage' pillar in the four "L"s of financial crises: Leverage, Liquidity, Losses and Linkage. They argue that measure of systemic risk must capture the degree of connectedness in the financial system to some extent because all truly systemic events involve financial system - the interactions and connections among financial stakeholders. These authors, however, do not differentiate connectedness from correlation, but instead, correlation is a form of connectedness, which is inherent in their measure of systemic risk using Principle Component Analysis. The object of connectedness in this case is monthly returns (for banks, brokers/dealers, insurance companies and hedge funds) instead of asset or liability. Diebold and Yilmaz (2015) also hold the view that return correlation is one popular measure of connectedness. However correlation has several limitations: it measures only linear, non directional and largely pairwise relationship. The non-linearity concern can be addressed by dependence measure using copula functions or time-varying conditional correlations these remain non-directional. Based on forecast variance decomposition of a VAR model, Diebold and Yılmaz (2014) propose several connectedness measures such as "from-others " and "to-others" connectedness to gauge the relative impacts individual nodes receive from or exert to others, pair-wise connectedness to measure the connection between two nodes and "total" connectedness to quantify the magnitude of connectedness of the whole system. The authors used the net pairwise directional connectedness con build a network among sixteen major financial institutions around the collapse of Lehman Brothers, in which out-ward links from Lehman to others are seen to increase significantly during its last two trading days. In foreign exchange market, Diebold and Yilma's approach (Diebold and Yılmaz, 2014) was employed mainly to gauge the direction connectedness and spillovers among currencies. For example, Diebold and Yilmaz (2015) analyzed the volatility connectedness for a sample of nine major currencies vis-a-vis USD; On the same set of currencies but longer time span, Greenwood-Nimmo et al. (2016) generalized the framework of Diebold and Yılmaz (2014) to analyze not only spillovers of risk neutral returns, risk neutral variance but also risk neutral skewness to capture the so-called 'crash risk'. Like in Diebold and Yılmaz (2014), the later study found that the total connectedness could capture major systemic events during the sub-prime crisis. Diebold and Yilma's framework is laid on sound theoretical foundation, easy to understand and apply, thus, is very popular. Nevertheless, their approach requires identifying assumptions relating to variance-decomposition and impulse response analysis which may affect ultimate findings. As a result, the approach may best used with volatility as the connected object (Diebold and Yilmaz, 2015)

Granger causality concept was introduced by Granger (1969), then extensively developed and applied in different disciplines. The idea of granger-causality-based network to financial markets is, perhaps, first proposed by Billio et al. (2012). The authors' approach can be considered as compatible to that of Diebold and Yılmaz (2014) but has two main limitations. First, the pairwise granger causality between the two returns X and Y may be spurious if it is driven by a common third return Z. This third series may enhance or block the relationship between X and Y (Lütkepohl, 1982). Second, their model used to estimate granger causality is bivariate, focusing on two variables alone, without considering the simultaneous effects of others. These causality relationships may not hold in the multivariate case. In his paper "Non-causality due to omitted variables", Lütkepohl (1982) proves theoretically and empirically that it is difficult or even impossible to draw conclusions about the relationship between two variables solely on the basis of a time series model just including these two. Blinowska et al. (2004) discovered several pitfalls in evaluating the direction of causal relations in physiological time series of electroencephalogram using bivariate techniques and hence emphasized the importance of a multivariate approach. As stated by Stern (1993), the advantage of multivariate Granger tests over bivariate Granger tests is that they can help avoid spurious correlations and can improve general validity of the causation test. These limitations are well addressed by employing multivariate conditional granger causality framework developed by Barrett et al. (2010) and Barnett and Seth (2014).

In short, returns or volatility connectedness among assets can be quantified by three approaches: correlations, dependence and cross spillovers.The third approach comprises two frameworks: Forecast variance decomposition (Diebold and Yılmaz, 2014) and Granger-causality (Billio et al., 2012). Our first contribution is to append the lead-lag spillovers approach in (Billio et al., 2012) using conditional granger causality as opposed to unconditional granger causality. Another contribution over (Billio et al., 2012) is that we not only investigate whether there is a connection between two assets or not but also how strong this connection is, conditional on the influences of others. Thirdly, we relates our measures of total connectedness with important macro-economic events and financial indicators like VIX, Vstoxx and TED spread to gain insights of this series before proposing it to be a potential global systemic risk indicator.

The second strand of literature is network of currencies. A network or graph (G) is generally understood as a collection of vertexes (V) and links (E) between them. Mathematically, this can be expressed as: $G = (V, E), V \subset \mathbb{N}, E \subset V \times V$. Applied to the field of finance, networks can represent specific markets, specific financial sectors or the financial system as a whole. Indeed, assets or institutions can be seen as nodes while relationships between them can be expressed as links or edges. Edges can be directional, weighted or both directional and weighted. From macro perspective, academics and practitioners rely on network approach to study financial stability, systemic risk and contagion. This approach helps to uncover a system's structure and connectedness, which play a vital role in systemic risk development, and helps to address the 'robust but fragile' issue. At micro level, investors can benefit from portfolio diversification and return forecast (Wang and Xie, 2016). Since there is a close relationship between foreign exchange market and other financial markets, studying connectedness and structure in global currency market is important. Investors and policy makers and have early warning signal or confirmation evidence regarding development of systemic risk in stock markets (Ortega and Matesanz, 2006; Jang et al., 2011).

Initially laying in the domain of graph theory, network science was first used by sociologist to study relationship between social entities in the 1920s, then expanded rapidly to a wide range of disciplines in the late 1990s sparked by the two influential papers on small world networks (Watts and Strogatz, 1998) and on scale-free networks (Barabási and Albert, 1999) along with the development in computer sciences (Fenn, 2010; Onnela et al., 2006). Literature about network studies in foreign exchange markets is vast, ranging from the earliest study in 2005 (McDonald et al., 2005) till the most recent in 2016 (Kireyev and Leonidov, 2016; Shahzad et al., 2017). Foreign exchange market operates 24 hours a day, on global scale, involving millions of participants and trillions of USD daily turnover. This make it nearly impossible to construct network of currencies using real transaction data. Almost all researchers, therefore, rely on exchange rates to visualize linkages between currencies and study different properties. Motivated by the work of Mantegna (1999) on US stock markets, McDonald et al. (2005) applied the Minimum Spanning Tree techniques to the correlation network of foreign exchange markets, focusing on 11 most liquid currencies. Based on multi-step survival analysis they found the correlations among exchange rate returns are extremely long-lived. Furthermore, several currency clusters are found. These clusters change over time as the minimum spanning tree itself changes. Clustered structure is also found in all studies using the same methods, for examples Ortega and Matesanz (2006), Kwapień et al. (2009), Jang et al. (2011) and Matesanz and Ortega (2014). Each cluster often comprise currencies from the homogeneous geographical regions Ortega and Matesanz (2006) centering around a key currency from a major economyMizuno et al. (2006). Dependence-based networks using time varying copula-t (Wang et al., 2014) and Symmetrized Joe-Clayton copula (Wang and Xie, 2016) provide similar conclusion on connectedness structure.

One similarity in the mentioned studies is that the networks are generally weighted but undirected. Granger-based causality approach in Billio et al. (2012) and Vỳrost et al. (2015) can address the directional problem but result in unweighted networks. Meanwhile, as argued by Diebold and Yilmaz (2015), both weight and direction of connectedness matter in real life. Two recent studies address this issue are those of Kireyev and Leonidov (2016) and Shahzad et al. (2017). Based on his proposed definition of currency demand indicator, Kireyev and Leonidov (2016) derives a multilateral exchange rate network from which the multilaterally equilibrium levels of bilateral exchanges rates are identified. However, their network may not reflect the dynamics of real world since the weights of links rely heavily on the share of currencies in the international currency turnover which only change every three years. Shahzad et al. (2017) propose a noteworthy approach when extending the connectedness to also the tail of return distribution. Accordingly, they use cross-quantilogram from Han et al. (2016) to measure the lead/lag directional return spillovers among a group of 20 currencies in different quantiles. Then, based on that, three different networks corresponding to three market states, namely bearish, normal and bullish, can be visualized. Together with other model-based approach using copula (Wang and Xie, 2016; Lee and Yang, 2014) or quantile regression (Chuang et al., 2009), this modeless approach can show how currencies are connected to each other in extreme market conditions, which is beneficial to portfolio managers. The limitation is that, how linkages on global scale vary continually over time in terms of number of links and their strength is unknown. Another limitation, is the directional spillovers are bivariate and pairwise, thus not taking for the moderating effects of other exchange rates and not considering the effects of one exchange rate to total and vice versa. Last but not least, the authors just focus on a group of 25 currencies, many of which are not representative for the global currency basket due to low trading volume.

In this paper, overall, we find that connectedness among global currencies exhibited dynamics through time on both breath dimension and depth dimension. Total connectedness witnessed unprecedented increase in banking and credit crisis period 2007 2012, structurally rose from the collapse of Lehman Brothers and structurally fell not long after the announcement of Outright Monetary Transactions of European Central Bank. The Lehman Brothers impact is also observed in most to-connectedness and from-connectedness series. One-step and multi-step survival ratios show that the links between two certain nodes, once established, were rather stable. In relation with some major financial indicators, spikes in the rolling connectedness were associated with rises in global risks and uncertainty reflected via VIX and TED spread: when VIX, rolling VIX and rolling TED reached their highest levels, so did the connectedness. Besides, correlations with VIX, rolling VIX and rolling TED spread were much higher than average during two crises. Thus, in light of Billio et al. (2012), network rolling connectedness could potentially be considered as an indicator of systemic risk. As for connectedness structure, global currencies tend to form different communities based on connection strength and density. There exist communities consisting of currencies sharing similar geographical locations; certain groups or pairs of currencies fall within one group in several sub-periods; and on average connection between currencies of emerging markets is the most dense. Similar to vast number of studies in literature, the degree of global currencies, both weighted and unweighted, follow power law distribution, though log-normal distribution is slightly better fitted. Finally, though no currency was uniquely most central in different sub-periods, currencies from advanced economies like Canada, Norway, Japan, the United Kingdom, Singapore, Korea, Taiwan frequently presented among the top most connected.

The rest of our paper is structured as follows: in Section 2 we outline the research methodology, notably on conditional Granger causality (G-causality), how a network is constructed and major network connectedness measures. G-causality and conditional G-causality framework in subsection 2.1 and 2.2 is drawn heavily from Barnett and Seth (2014). Section 3 presents empirical data, research findings and discussions. Conclusion, limitations and directions for future research are covered in section 4.

2. Methodology

2.1. VAR process theory

Given two jointly-distributed random variables X and Y. X is said to Granger causes Y if the past of X can help to predict Y beyond information already contained in the past of Y itself. In the multivariate setting, G-causality between variables is often estimated in a vector autoregressive model with p lags - VAR(p), which takes the form:

$$\mathbf{U}_t = \sum_{k=1}^{p} \mathbf{A}_k.\mathbf{U}_{t-k} + \varepsilon_t \tag{1}$$

Here p is the model order, $\mathbf{A}_k$ is $n \times n$ matrix of regression coefficients, ε_t the $n \times 1$ vector of residuals and k is the optimal lag selected using Bayesian Information Criterion (BIC) or Akaike Information Criterion (AIC). According to Lütkepohl (2005), for G-causality to be valid, the VAR coefficients in 1 must be square summable and stable. Intuitively, square summability requires the coefficients do not "blow up", even when the model order $p \longrightarrow \infty$ (Barnett and Seth, 2014). Stability means that the coefficient matrix $\mathbf{A}_k$ defines a covariance-stationary process, for which, the following condition must be satisfied:

$$det(I_k - A_1 z - A_2 z^2 - ... - A_k z^k) \neq 0 \qquad for \ \ |z| \leqslant 1 \tag{2}$$

with the variable z defined in the complex plane $\mathbb{C}$.

2.2. Linear Granger causality

2.2.1. Unconditional causality

Suppose U_t in equation (1) is split into two jointly distributed processes:

$$U_t = \begin{pmatrix} Y_t \\ X_t \end{pmatrix} \tag{3}$$

Then equation (1) can be decomposed as:

$$\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \sum_{k=1}^{p} \begin{pmatrix} A_{yy,k} & A_{yx,k} \\ A_{xy,k} & A_{xx,k} \end{pmatrix} \begin{pmatrix} Y_{t-k} \\ X_{t-k} \end{pmatrix} + \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{x,t} \end{pmatrix} \tag{4}$$

and the residuals covariance matrix as

$$\sum \equiv cov \begin{pmatrix} \varepsilon_{y,t} \\ \varepsilon_{x,t} \end{pmatrix} = \begin{pmatrix} \sum_{yy} & \sum_{yx} \\ \sum_{xy} & \sum_{xx} \end{pmatrix} \tag{5}$$

The y-component of the regression (4) is:

$$Y_t = \sum_{k=1}^{p} A_{yy,k}.Y_{t-k} + \sum_{k=1}^{p} A_{yx,k}.X_{t-k} + \varepsilon_{y,t} \tag{6}$$

In equation (6) the coefficients $\mathbf{A}_{yx,k}$ encapsulate the dependence of $\mathbf{Y}$ on past of $\mathbf{X}$ given its own past. Thus, there is no dependence of $\mathbf{Y}$ on the past of $\mathbf{X}$ if and only if $A_{yx,1} = A_{yx,2} = ... = A_{yx,p} = 0$. This motivates us to consider the following reduced regression, formed by omitting the past of X:

$$Y_t = \sum_{k=1}^{p} A'_{yy,k} + \varepsilon'_{y,t} \tag{7}$$

Here $A'_{yy,k}$ and $\varepsilon'_{y,t}$ are relatively the coefficients and residuals of the reduced regression model.

Let $\mathcal{F}_{X \longrightarrow Y}$ be the G-causality from X to Y. $\mathcal{F}_{X \longrightarrow Y}$, by definition, reflects the degree to which the past of X can help to predict Y beyond past information of Y itself. Now $\mathcal{F}_{X \longrightarrow Y}$ also quantifies the degree to which the full regression model (6) represents a better model of the data than the reduced regression model (7) (Barnett and Seth, 2014), which can be calibrated as follows in the spirit of Geweke (1984):

$$\mathcal{F}_{X \longrightarrow Y} \equiv ln \frac{|\sum'_{yy}|}{|\sum_{yy}|} \tag{8}$$

where $\sum_{yy} = cov(\varepsilon_{y,t})$ and $\sum'_{yy} = cov(\varepsilon'_{y,t})$ are the residuals covariance matrices of models (6) and (7); $|\sum|$ is the determinant of the the residuals covariance matrix of a VAR model in the form (1), called the *generalized variance* (Barnett and Seth, 2014). Judging on several grounds like transformation invariance, frequency decomposition, information-theoretic interpretation and consistency with the maximum likelihood formation, Barrett et al. (2010) argue that generalized variance is an appropriate measure of *model prediction error*. Thus, G-causality in (8) gauges the reduction in prediction error when the past of $\mathbf{X}$ is is included to predict $\mathbf{Y}$. As asymptotically equivalent to information-theoretic transfer entropy (Barnett and Bossomaier, 2012), G-causalities can be meaningfully compared with due attention to statistical significance (Barnett and Seth, 2014).

2.2.2. Conditional Granger causality

The problems of spurious causality is originally mentioned in Granger (1969) and investigated by several authors including Geweke (1984), Chen et al. (2006), Eichler (2007), Barrett et al. (2010) and Barnett and Seth (2014). Granger (1969) was the first to coin the term 'spurious causality', referring to the case when relevant data and information is not available in causal relationship between two variables. According to Chen et al. (2006) the original definition of causality in Granger (1969) is applied to two stationary random variables, when a third series is taken into account, prima facie cause is used to describe the true causal relationship. $\mathbf{X}$ is said to prima facie causes $\mathbf{Y}$ if the observations of $\mathbf{X}$ up to time t help one predict $\mathbf{Y}_{t+1}$ when the corresponding observations of $\mathbf{X}$ and $\mathbf{Z}$ are available (Granger, 1980). Geweke (1984) is perhaps the first to mention the term conditional causality and the first to officially provide a testable solution to conditional causality. Conditional GC model is further developed and applied widely in several fields, especially neuro-science (Chen et al., 2006; Barrett et al., 2010). Chen et al. (2006) furthered the work of Geweke (1984) and applied to multivariate neural field potential data. Eichler (2007) tried to visualize the multivariate conditional causal relationships in graphs. Barrett et al. (2010) argued that traditional bivariate method may lead to fake causality and gave proof to the unification of time domain and frequency domain. These authors' theoretical framework is well presented in Barnett and Seth (2014) together with Matlab toolbox to efficiently estimate conditional Granger causality.

Suppose the universe of $\mathbf{U}$ in (1) splits into three jointly distributed multivariate processes:

$$\mathbf{U}_t = \begin{pmatrix} \mathbf{Y}_t \\ \mathbf{X}_t \\ \mathbf{Z}_t \end{pmatrix} \tag{9}$$

To condition out the effect of $\mathbf{Z}$, base on VAR(p) framework, we consider the following full and reduced regressions:

$$\mathbf{Y}_t = \sum_{k=1}^{p} A_{yy,k}.\mathbf{Y}_{t-k} + \sum_{k=1}^{p} A_{yx,k}.\mathbf{X}_{t-k} + \sum_{k=1}^{p} A_{yz,k}.\mathbf{Z}_{t-k} + \varepsilon_{y,t} \tag{10}$$

$$\mathbf{Y}_t = \sum_{k=1}^{p} A'_{yy,k}.\mathbf{Y}_{t-k} + \sum_{k=1}^{p} A'_{yz,k}.\mathbf{Z}_{t-k} + \varepsilon'_{y,t} \tag{11}$$

The causality from **X** to **Y** conditioned on **Z**, denoted as , is:

$$\mathcal{F}_{\mathbf{X}\longrightarrow\mathbf{Y}|\mathbf{Z}} \equiv ln\frac{|\sum'_{yy}|}{|\sum_{yy}|} \tag{12}$$

Note that the null hypothesis test of no causality is still:

$$Ho : A_{yx,1} = A_{yx,2} = ... = A_{yx,p} = 0 \tag{13}$$

but in this case, **Z** is included in both reduced and full regression models to account for its joint effect. Thus $\mathcal{F}_{\mathbf{X}\longrightarrow\mathbf{Y}|\mathbf{Z}}$ can be interpreted as "the degree to which the past of **X** helps predict **Y** beyond the degree to which **Y** is already predicted by its own past and the past of **Z**" (Barnett and Seth, 2014). In case X and Y are two individual variables, we have pairwise conditional G-causality (PWGC). When X and Y both contains a group of variables, we have multivariate conditional G-causality (MVGC). MVGC is used to estimate return spillovers among currency groups, taking into account within group interactions, while PWGC is used to construct weighted and directed networks of currencies, following (Billio et al., 2012).

2.3. Network connectedness

In this research, weighted, directed networks are constructed based on PWGC. The idea is as follows: each exchange rate is treated as a NODE; if exchange rate y Granger causes exchange rate x conditional on a set of other exchange rates z, then there is a directional link or directional EDGE from node y to node x and $F_{x\longrightarrow y|z}$ becomes the WEIGHT of this link or edge.

2.3.1. Node centrality

Once the network is constructed, the first important task is to investigate the centrality of the exchange rates to determine which are the most connected. To this aim, we use the following centrality criteria:

Node degrees. Node degree measures the total number of links a particular node has. In a directed network, the degree of a node includes in-degree and out-degree. In-degree is the sum of all links that point to the node. Out-degree, on the contrary, is the sum of all links that depart from the node.

Node strength. Node strength is the weighted sum of all links that a node has. Like node degree, node strength of a directed network comprises of node out-strength and node in-strength. Node out-strength measures the weighted sum of links that go out of a node whereas node in-strength is the weighted sum of links that go into a node. In Diebold and Yılmaz (2014) node strength is also named total connectedness, node out-strength called to-other-connectedness whereas node in-strength called from-other-connectedness.

Betweenness centrality. Node betweenness centrality is the fraction of all shortest paths in the network that contain a given node.

$$B(y) = \sum_{s \neq y \neq t \in V} \frac{\sigma_{st}(y)}{\sigma_{st}} \tag{14}$$

where σ_{st} denotes shortest path from node s to node t, $\sigma_{st}(y)$ denotes shortest path from node s to node t that contains node y, V is the set of nodes in the network G. Nodes with high values of betweenness centrality participate in a large number of shortest paths. In some sense, it measures the influence a node has over the spread of information through the network (Newman, 2010).

Closeness centrality. Closeness centrality (or closeness) of a node is a measure of centrality in a connected network. It is often calculated as the reciprocal sum of the length of the shortest paths between the node and all others.

$$C(y) = \sum_{y \neq x} \frac{1}{d(y,x)} \tag{15}$$

where *d(y,x)* is the shortest path form node y to node x. The more central a node is, the closer it is to all other nodes. Quantitatively, nodes with lowest $\sum_{y \neq x} d(y,x)$, or highest C will have highest centrality.

Harmonic closeness centrality: is the sum of the reciprocal of shortest path from a particular node to others, where the reciprocal equal to zero if there exist no path (Rochat, 2009).

$$H(y) = \sum_{d(y,x)<\infty, y \neq x} \frac{1}{d(y,x)} \tag{16}$$

Here the closeness centrality formula is modified to encompass the case of disconnected network. If there exist no path from node y to node x, $d(y,x) = \infty$, we set $1/d(y,x) = 0$. However, care must be exercised when interpreting the final results, especially on nodes having only one out-degree in unweighted directed network. In this study we adjust the numerator of Rochat's formula to become the average shortest path, as follows:

$$H(y) = \sum_{d(y,x)<\infty, y \neq x} \frac{n}{d(y,x)} \tag{17}$$

where n is the number of shortest paths reachable. *Eigenvector centrality.* Eigenvector centrality measures the importance of a node in a network depending upon the importance of nodes it is connected to. Eigenvector centrality is therefore a self-referential measure of centrality: nodes have high eigenvector centrality if they connect to other nodes that have high eigenvector centrality. According to (Glasserman and Young, 2016; Billio et al., 2012), the eigenvector centrality ϑ_y of node y satisfies

$$\lambda \vartheta_y = \sum_{x=1}^{N} \vartheta_x A_{xy} \tag{18}$$

where A_{xy} is an adjacency matrix.
In a directed network, we have left and right eigenvector centrality. Left eigenvector centrality of node y is the sum of the eigenvector centralities of nodes that conditionally Granger-cause y. Whereas right eigenvector centrality is the sum of the eigenvector centralities of nodes Granger-caused by y, conditional on others.

2.3.2. Connectedness distribution

Once degrees, both weighted and unweighted, of all nodes are obtained, we then examine the network degree distribution or in fact, the distribution of node connectedness. It is widely documented that degrees of several real-life networks follow power law distribution, for example distribution of hyper-links in the World Wide Web (Barabási and Albert, 1999), words frequency, citations of scientific papers (Newman, 2005), the populations of cities, the intensities of earthquakes, and the sizes of power outages (Clauset et al., 2009), degree of world currency network (Górski et al., 2008; Kwapień et al., 2009; Wang and Xie, 2016). Clauset et al. (2009) document two types of power law distributions, including continuous and discrete. The continuous version has probability density function:

$$p(x) = \frac{\alpha - 1}{x_{min}} \left(\frac{x}{x_{min}} \right)^{-\alpha} \tag{19}$$

where $\alpha > 1$ and $x_{min} > 0$. The probability mass function for the discrete case is:

$$P(X = x) = \frac{x^{-\alpha}}{\zeta(\alpha, x_{min})} \tag{20}$$

where

$$\zeta(\alpha, x_{min}) = \sum_{n=0}^{\infty} (n + x_{min})^{-\alpha} \tag{21}$$

is the generalized zeta function. A typical α normally falls within the range $[2; 3]$ (Newman, 2005).

2.3.3. Connectedness structure

Network analysis does not only investigate properties of nodes but also explore the connectedness structure or topology of the network. The importance of network topology is contended by Anderson and Moore (2006) regarding resilience to external attacks:

> "Network topology can strongly influence conflict dynamics. Different topologies have different robustness properties with respect to various attacks".

According to Estrada (2007), real-life networks exist in one of the four following structures: *good expander* (highly homogeneous networks lacking structural bottlenecks), *modular network* (networks organized into highly interconnected modules with low inter-community connectivity), *core-periphery* (networks with a highly connected central core surrounded by a sparser periphery, and *network with holes* (Csermely et al., 2013). Among these four, core-periphery and modularity are found to be one of two common features of social and economic networks

(Hojman and Szeidl, 2008). However, the difference between core-periphery and modular structure is not clear cut (Csermely et al., 2013), but largely depending on the organization of communities in the network (Estrada, 2007).

2.3.4. Connectedness stability

Connectedness stability among exchange rates is examined using single-step survival ratio and multi-step survival ratio following Onnela et al. (2006). Denote $E_{(t)}$ as a set of edges of the conditional Granger causality network at time t. Single-step survival ratio at time t is defined as:

$$SSR(1,t) = \frac{E_{(t)} \cap E_{(t-1)}}{E_{(t-1)}} \tag{22}$$

Multi-step survival ratio at time t is then:

$$MSR(s,t) = \frac{E_{(t)} \cap E_{(t-1)} \cap E_{(t-2)} ... \cap E_{(t-s)}}{E_{(t-s)}} \tag{23}$$

where s is the number of steps.

3. Empirical data and results

3.1. Data

To minimize missing data and ensure global characteristics we focus on 35 most traded currencies surveyed by BIS (2016) in the period from 1999 to 2017. It is reported from successive BIS triennial surveys from 2001 to 2016 that trading volumes of these currencies account for around $96 - 99.8\%$ of global daily transactions. From the list of these currencies, we have a sample of 34 exchange rates against USD. We choose USD as the base currency following several studies and because USD is the most liquid, most traded and most important reserve currency world-wide. Furthermore, trading between these currencies against USD accounts for around 80% of all pairs. We will use EUR for robust study, acknowledging that numeraire currencies could effect analysis results. Multilateral exchange rates like nominal effective exchange rates (NEER) are not utilized since we believe that interactions among bilateral exchange rates better capture and more timely reflect concurrent processes in the foreign exchange market, effects from other financial markets and especially behaviours of investors. In similar vein, the Special Drawing Rights (SDR) of the International Monetary Funds is also not considered as it has little business meaning. Data is taken from Bloomberg terminal. The rates are mid-point spot exchange rates at the end of each day based on the calendar of the United States. Missing data for non-trading days in US is filled using last-price carry-forward principle. It is obvious from the list of currencies in Table 1 that our sample is unbalanced in terms of continents with strong bias towards Europe and Asia while South African Rand (SAR) is the only representative of African currencies.

A more balanced way to structure these 34 currencies is to group them corresponding to the level of development of countries that issue them. Accordingly we have two broad groups: advanced economies (16) and emerging economies (18).

As advanced or emerging economies are also heterogeneous, we further divide them into: Group of Eleven (G11), Other Advanced Economies (OAE) Emerging Leading and Growth economies (EAGLES), and Other Emerging Economies (OEE). G1O includes ten currencies of developed countries: EUR, JPY, GBP, AUD, CAD, CHF, SEK, NZD, NOK and DKK. OAE comprises of six currencies from Singapore, Hong Kong, Taiwan, South Korea, Czech Republic and Israel (IMF, 2017). Nine currencies that fall into EAGLES are: BRL, RUB, INR, CNY, MXN, IDR, PHP, MYR and TRY. The rest nine currencies belong to other emerging economies group.

To gauge the dynamics of global currency connectedness, besides using rolling samples, we divide the whole period into six subsamples namely: 1999-2002, 2003-2007, 2007-2009, 2009-2012, 2012-2015 and 2016-2017. The first subsample begins from the lauch of EUR, covering the dot-com bubble and the economic recession 2001. The second subsample is arguably the period of economic expansion in the US and world major economies. The third and fourth sub-periods are global financial crisis and European sovereign debt crisis. The first crisis lasts from 03 July 2007 to 14 May 2009 as suggested by Dungey et al. (2015) while the latter dates back to 16 October 2009, coinciding with the revising upwards of Greece's budget deficit to 12.5% of its GDP, and ends on 12 September 2012 when the European Stability Mechanism got the go-ahead from a German court. The fifth sub-sample serves as after-crisis period while the period from 01 January 2016 till the end of 2017 tracks recent historic events and trends including Brexit, populism in Europe and United States and rising protectionism. In this research, we use log return because it is considered as continuous compounded return, quite similar to simple return on daily basis but has advantage of being time additive (Hudson and Gregoriou, 2015). The equation for daily log return is as follows:

$$r_{i,t} = ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \times 100 \tag{24}$$

where $r_{i,t}$ is the daily log return of currency i at time t, $P_{i,t}$ and $P_{i,t-1}$ are exchange rates of currency i against USD at time t and $t-1$ relatively.

Basic information about characteristics of these series is provided in Table 1.The mean daily log returns of all currencies are not significantly different from zero with exception of TRY, RON and CNY. Mean daily returns of TRY and RON are significantly positive value while that of CNY is significantly negative. This means that on average CNY have more daily appreciation against USD than the other way round and vice-versa for TRY and RON. All log returns series exhibit excess skewness, especially excess kurtosis. Excess kurtosis or fat tail implies high likelihood of extreme values are expected with all series, especially TRY, PHP, SAR and CHF. The Turkish lira,TRY, also has highest excess skewness,

Table 1: **Descriptive statistics of foreign exchange rate returns**

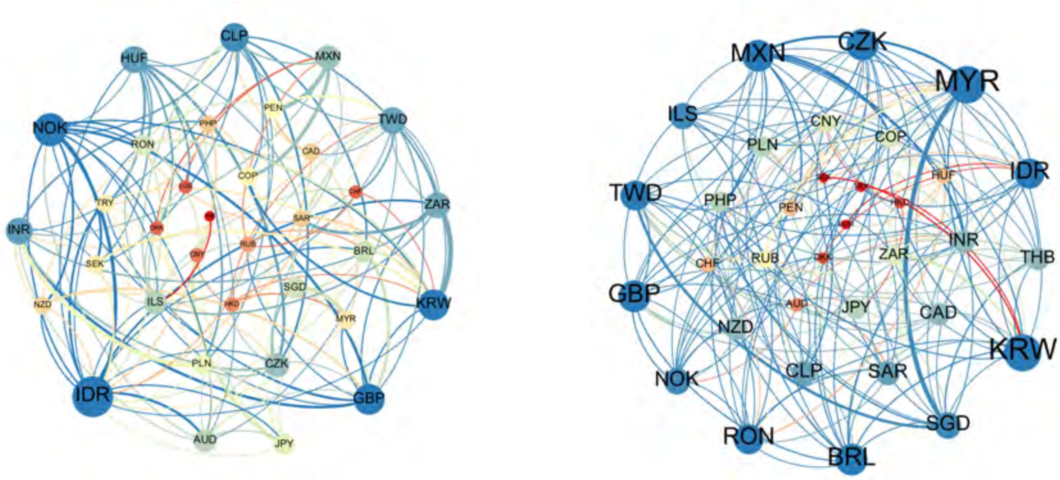
Code	Currencies	Obs	Min	Max	Mean	Median	Stdev	Skew	Kurtosis	J-B test	ADF test
AUD	Australian dollar	4752	-7.94	7.31	0.00	-0.04	0.82	0.40	8.67	***	***
NZD	New Zealand dollar	4752	-4.29	6.52	-0.01	-0.03	0.83	0.36	2.60	***	***
ZAR	South African Rand	4752	-6.63	15.50	0.02	-0.02	1.10	0.90	10.96	***	***
BRL	Brazilian real	4752	-10.34	8.70	0.02	0.00	1.12	0.25	10.15	***	***
CAD	Canadian dollar	4752	-4.00	3.61	0.00	-0.01	0.57	0.16	3.02	***	***
COP	Colombian peso	4752	-7.60	6.02	0.01	0.00	0.72	0.03	9.14	***	***
CLP	Chilean peso	4752	-5.09	4.68	0.01	0.00	0.63	0.29	5.26	***	***
MXN	Mexican peso	4752	-6.14	7.98	0.01	-0.01	0.71	0.85	11.80	***	***
PEN	Peruvian new sol	4752	-2.85	2.32	0.00	0.00	0.29	0.09	13.92	***	***
CHF	Swiss franc	4752	-19.38	8.95	-0.01	0.00	0.74	-3.49	103.99	***	***
CZK	Czech koruna	4752	-4.67	5.33	-0.01	-0.01	0.78	0.15	3.21	***	***
DKK	Danish krone	4752	-3.50	2.77	0.00	-0.01	0.64	-0.01	1.44	***	***
EUR	Euro	4752	-3.48	2.77	0.00	-0.01	0.64	-0.01	1.42	***	***
GBP	Pound sterling	4752	-2.92	8.44	0.00	0.00	0.59	1.05	12.34	***	***
HUF	Hungarian forint	4752	-5.50	6.86	0.00	0.00	0.91	0.40	4.12	***	***
ILS	Israeli new shekel	4752	-2.68	3.00	0.00	0.00	0.48	0.22	4.14	***	***
NOK	Norwegian krone	4752	-4.97	4.87	0.00	-0.01	0.77	0.19	2.52	***	***
PLN	Polish zloty	4752	-6.55	7.53	0.00	-0.03	0.88	0.35	5.31	***	***
RON	new Romanian leu	4752	-6.54	12.63	0.03	0.03	0.76	1.24	23.78	***	***
RUB	Russian rouble	4752	-17.35	17.00	0.02	0.00	0.82	0.62	91.54	***	***
SEK	Swedish krona	4752	-4.98	5.32	0.00	-0.01	0.77	0.11	2.71	***	***
TRY	Turkish lira	4752	-8.28	35.69	0.05	0.00	1.11	7.75	236.91	***	***
CNY	Chinese yuan	4752	-2.03	1.83	-0.01	0.00	0.11	-0.63	54.35	***	***
HKD	Hong Kong dollar	4752	-0.61	0.31	0.00	0.00	0.03	-2.00	48.84	***	***
INR	Indian rupee	4752	-3.32	3.97	0.01	0.00	0.39	0.50	12.05	***	***
IDR	Indonesian rupiah	4752	-8.98	8.80	0.01	0.00	0.76	-0.24	20.99	***	***
JPY	Japanese yen	4752	-3.78	5.50	0.00	0.00	0.66	-0.05	3.65	***	***
KRW	Korean won	4752	-13.24	10.26	0.00	-0.01	0.67	-0.81	53.12	***	***
MYR	Malaysian ringgit	4752	-3.47	1.99	0.00	0.00	0.35	-0.33	8.52	***	***
PHP	Philippine peso	4752	-11.10	3.15	0.01	0.00	0.41	-4.41	121.14	***	***
SAR	Saudi riyal	4752	-0.56	0.59	0.00	0.00	0.02	1.75	211.05	***	***
SGD	Singapore dollar	4752	-2.38	2.67	0.00	-0.01	0.34	0.03	4.15	***	***
TWD	new Taiwan dollar	4752	-2.62	2.19	0.00	0.00	0.26	-0.05	8.95	***	***
THB	Thai baht	4752	-3.31	3.81	0.00	0.00	0.34	0.14	11.08	***	***

which translates into this currency having very high likelihood of extreme one day depreciation against USD. While BRL shows highest standard deviation of returns, daily volatility and the range of daily returns for HKD and SAR belong to top lowest group. This is reasonable since SAR and HKD is pegged against USD while CNY is managed floating with strong intervention from the People's Bank of China.

Table 1 also shows all return series are stationary, thus fit for our analysis. The fact that Jacques - Berra test for normality is strongly rejected fits with properties of skewness and kurtosis, implying normal distribution is not appropriate to model exchange rate returns.

3.2. Node connectedness

Figure 3 provides some intuitions on which exchange rates are most connected during the whole research period as well as in sub-periods. In the sub-figures, each filled circle represents a node, each curve represent a directional link between two nodes following clock-wise direction. For example, in Figure 1b, the blue curve between SGD and MYR indicates an edge originating spillover from SGD to MYR, the red curve between HKD and KRW the two represents a spillover from HKD to KRW. The bigger the circle, the higher the total strength of a node and similarly, the thicker the edge, the higher the weight or magnitude of spillovers. Edges' colors take colors of the source nodes. Regarding nodes' colors, the bluer the nodes, the higher their degrees.



(a) 2007 – 2012 (b) 1999 – 2017

Figure 1: **Networks of global currencies**

3.2.1. Node centrality

Node centrality shows which nodes are the most connectedness in the web of connections. To this end, we first combine total degree, total strength and betweenness centrality to judge the total connectedness of a particular node. Betweenness centrality can go with total degree and total strength since high ranking on this criterion requires a node to have both inward links and outward links to be on most shortest paths between two any other nodes. Table 2 provides a rather mixed picture on which node is the most central for each period of time. For instance, over the period 1999 - 2017, total degree indicates that MYR is the most connected while total strength picks KRW, betweenness points to ZAR. A combination of these three criteria is thus appropriate for final judgment. Only those which appear in the top 10 of three criteria are considered. Accordingly, it is easy to tell that MYR is the most central for the whole sample, RUB for 1999-2002, CLP for 2007-2009, IDR for 2007-2012 and 2016 - 2017 and finally KRW for 2012-2015. However, in other periods, it is not so clear cut. For 2003-2007, it is hard to tell which between MXN and JPY are the most connected. For 2009 - 2012, it should be the competition between SGD and CAD. Overall we can see that the most connected currencies mostly falls onto 2 groups: EAGLES or Advanced economies, where EAGLES is more dominant. It is reasonable for positions of RUB and JPY in 1999-2001, JPY in 2003-2007 given the effects of Russian Default of 1998 and Japanese Quantitative Easing in early 2000s (Fawley et al., 2013). The centrality of MXN in 2003-2007 is also understandable thanks to the special relationship between Mexico and the United States, thus enjoyed the benefits from US' economic expansion in this period. Similarly, highest connectedness rankings of CLP, GBP, TWD, AUD in 2007 - 2009 are expected because of close trade and investment relationship between Chile, the United Kingdom, Taiwan, Australia with the United States. G11 currencies marked their presence in chaotic periods from 2007 to 2015 and uncertain period over the last two years. We can see currencies from this group in the top five of all criteria in these 4 sub-periods. It is also interesting to see that the two currencies most affected by Brexit, namely EUR and GBP make their ways to top 5 most central currencies in 2016-2017. The presence of CNY in the top 10 these last two years also fit with the efforts of China to turn CNY into a global currency, coinciding with the fact that CNY was included into the currency basket for SDR by the International Monetary Funds from 1 October 2016.

Another thing we are interested in is which currency is the most influential, in the way that changes in its value will quickly and strongly affect others. To answer this question, we opt to use right-hand eigenvector centrality, Harmonic closeness centrality, out-degree and out-strength. To save space, we only consider three periods: whole sample, the crisis period and the most recent period. Table 3 lists the top 10 currencies with regards to these four criteria. Fortunately these four criteria seem to provide very consistent ranking: they agree with each other in nearly 80% of the top 10 ranking. While out-degree tells how many nodes that a particular node can affect, out-strength provides information about strength of effect, harmonic closeness shows the influence speed and right-hand eigenvector centrality states the importance of nodes that are influenced. Overall, MXN, BRL and CZK are the three most influential. For the double crisis period, these go to IDR, CLP and NOK. While CAD is obviously most significant over the last two years. Again we see the presence of G11 currencies in top 5 most influential currencies in all periods considered, among them CAD and NOK is the most found then come GBP. EUR is also seen in the last period considered, together with CNY and SGD.

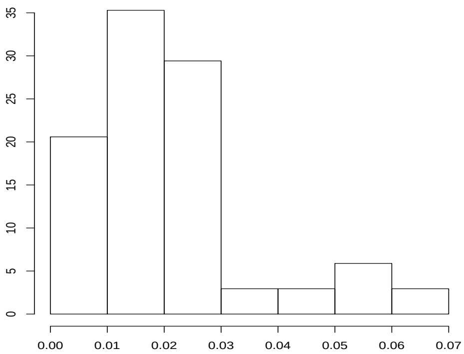
Table 2: **Node Total connectedness**

Criteria	Ranking	1999/17	1999/02	2003/07	2007/09	2009/12	2007/12	2012/15	2016/17
	1	**MYR**	**RUB**	**MXN**	**CLP**	**SGD**	**IDR**	**KRW**	**IDR**
	2	SGD	RON	MYR	GBP	TWD	NOK	SGD	CAD
	3	MXN	JPY	PHP	NOK	KRW	KRW	THB	SGD
	4	KRW	INR	COP	TWD	**CAD**	GBP	TWD	NOK
	5	TWD	PEN	**KRW**	AUD	MYR	CLP	MXN	GBP
Degree	**6**	ZAR	PLN	RON	HUF	IDR	INR	MYR	KRW
	7	INR	HUF	RUB	NZD	ZAR	HUF	**IDR**	MYR
	8	GBP	KRW	JPY	KRW	NOK	TWD	HKD	ZAR
	9	BRL	THB	IDR	MXN	THB	ZAR	PHP	CNY
	10	CZK	EUR	TWD	INR	COP	CZK	COP	MXN
	1	KRW	JPY	**MXN**	**CLP**	**SGD**	**IDR**	**KRW**	**IDR**
	2	**MYR**	**RUB**	RON	TWD	**CAD**	CLP	THB	NOK
	3	BRL	INR	**KRW**	AUD	NOK	NOK	MXN	CAD
	4	CZK	PLN	PHP	GBP	TWD	TWD	HKD	SGD
	5	GBP	PEN	**JPY**	KRW	KRW	GBP	**IDR**	GBP
Strength	**6**	MXN	RON	RUB	HUF	ZAR	KRW	SGD	MYR
	7	IDR	HUF	BRL	NOK	IDR	ILS	COP	ZAR
	8	RON	BRL	MYR	NZD	MYR	HUF	TWD	KRW
	9	TWD	THB	COP	IDR	THB	AUD	PHP	CNY
	10	ILS	CNY	CNY	BRL	INR	INR	MYR	HUF
	1	ZAR	**RUB**	**JPY**	TWD	**CAD**	**IDR**	**IDR**	**IDR**
	2	CLP	PEN	RUB	**CLP**	HKD	ILS	SEK	SGD
	3	TWD	JPY	**KRW**	MYR	TWD	TWD	THB	EUR
	4	**MYR**	BRL	BRL	BRL	THB	CLP	CHF	CNY
	5	ILS	INR	COP	AUD	MYR	AUD	CAD	ZAR
Betweenness	**6**	KRW	NZD	TRY	SGD	**SGD**	CZK	EUR	RUB
	7	CZK	PLN	CNY	COP	NOK	RON	**KRW**	TRY
	8	IDR	NOK	RON	GBP	SAR	MXN	PHP	CHF
	9	NZD	HUF	**MXN**	KRW	CNY	RUB	ILS	COP
	10	BRL	CHF	IDR	NOK	COP	GBP	NOK	MYR

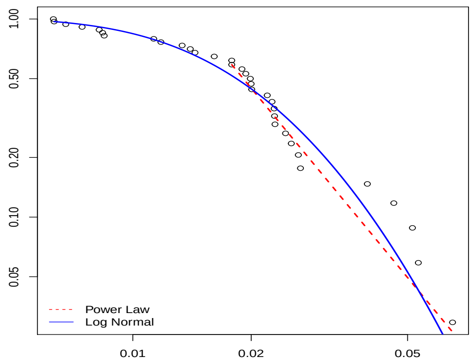
Table 3: **Node Influence**

Ranking	1999-2017				2007 - 2012				2016 - 2017			
	Eigen	CloseH	Deg.O	Streng.O	Eigen	CloseH	Deg.O	Streng.O	Eigen	CloseH	Deg.O	Streng.O
1	**BRL**	**CZK**	**BRL**	SGD	**IDR**	**IDR**	**IDR**	**NOK**	**CAD**	ILS	**NOK**	**CAD**
2	CZK	**MXN**	**MXN**	**MXN**	**CLP**	**CLP**	**CLP**	HUF	**CNY**	**CAD**	**CAD**	**SGD**
3	JPY	**NOK**	CZK	ZAR	**NOK**	**NOK**	**NOK**	**IDR**	SGD	**CNY**	SGD	**NOK**
4	**MXN**	NZD	**CAD**	**BRL**	HUF	TWD	HUF	**CLP**	EUR	SGD	ZAR	ZAR
5	ILS	**CAD**	**NOK**	**NOK**	TWD	HUF	**GBP**	ZAR	**NOK**	**NOK**	**IDR**	**IDR**
6	**NOK**	CLP	SGD	**CAD**	**CAD**	AUD	TWD	MXN	HUF	EUR	HUF	BRL
7	TWD	ILS	NZD	CZK	AUD	**CAD**	**CAD**	**GBP**	**IDR**	**IDR**	GBP	GBP
8	**CAD**	SGD	GBP	JPY	**GBP**	**GBP**	ILS	TWD	BRL	HUF	BRL	HUF
9	GBP	TWD	ILS	RUB	PLN	NZD	CZK	JPY	GBP	BRL	**CNY**	**CNY**
10	NZD	**BRL**	RUB	NZD	NZD	CZK	AUD	SGD	CHF	ZAR	MXN	MXN
11	RUB	RUB	TWD	ILS	BRL	ILS	ZAR	CAD	KRW	GBP	EUR	EUR
12	SGD	JPY	CLP	KRW	ILS	BRL	MXN	CZK	MXN	MXN	CLP	CLP
13	CLP	HUF	JPY	GBP	JPY	PLN	NZD	ILS	ZAR	CHF	RUB	RUB
14	AUD	AUD	KRW	TWD	RUB	RUB	JPY	PLN	TRY	KRW	HKD	THB
15	SAR	GBP	RON	PLN	TRY	MXN	SGD	AUD	THB	TRY	THB	HKD
16	ZAR	ZAR	ZAR	HUF	CZK	JPY	BRL	BRL	RUB	THB	DKK	DKK
17	KRW	MYR	HUF	CLP	MYR	ZAR	HKD	RON	COP	RUB	JPY	TRY
18	CNY	RON	PLN	RON	PHP	MYR	PLN	NZD	CLP	CLP	ILS	INR
19	RON	SAR	AUD	SAR	SGD	TRY	RON	HKD	MYR	COP	CHF	AUD
20	MYR	THB	MYR	COP	RON	SGD	SAR	SAR	AUD	MYR	AUD	COP
21	CHF	CNY	SAR	MYR	MXN	RON	TRY	SEK	DKK	AUD	TRY	MYR
22	HUF	PLN	CHF	THB	ZAR	PHP	RUB	RUB	INR	JPY	COP	ILS
23	HKD	KRW	CNY	IDR	SEK	HKD	PHP	TRY	SAR	HKD	MYR	CHF
24	IDR	CHF	IDR	AUD	KRW	SEK	CHF	PHP	PEN	DKK	INR	KRW
25	THB	HKD	PEN	PEN	COP	KRW	COP	PEN	HKD	INR	KRW	JPY
26	PLN	IDR	THB	CHF	HKD	COP	MYR	KRW	SEK	PEN	PEN	PEN
27	PEN	PEN	COP	INR	PEN	PEN	PEN	INR	RON	PLN	PLN	SAR
28	COP	COP	HKD	SEK	SAR	SAR	INR	COP	PHP	SEK	SAR	PLN
29	SEK	SEK	DKK	CNY	INR	CHF	KRW	CHF	CZK	SAR	TWD	TWD
30	TRY	TRY	EUR	HKD	CHF	THB	SEK	MYR	JPY	PHP	CZK	PHP
31	EUR	DKK	INR	EUR	EUR	EUR	THB	DKK	ILS	TWD	PHP	SEK
32	DKK	EUR	SEK	TRY	DKK	DKK	DKK	THB	NZD	CZK	SEK	CZK
33	INR	INR	TRY	DKK	THB	INR	EUR	EUR	PLN	NZD	NZD	RON
34	PHP	PHP	PHP	PHP	CNY	CNY	CNY	CNY	TWD	RON	RON	NZD

3.2.2. Degree distribution



(a) Frequency of Total Weighted Degree



(b) Power Law and Log Normal fit

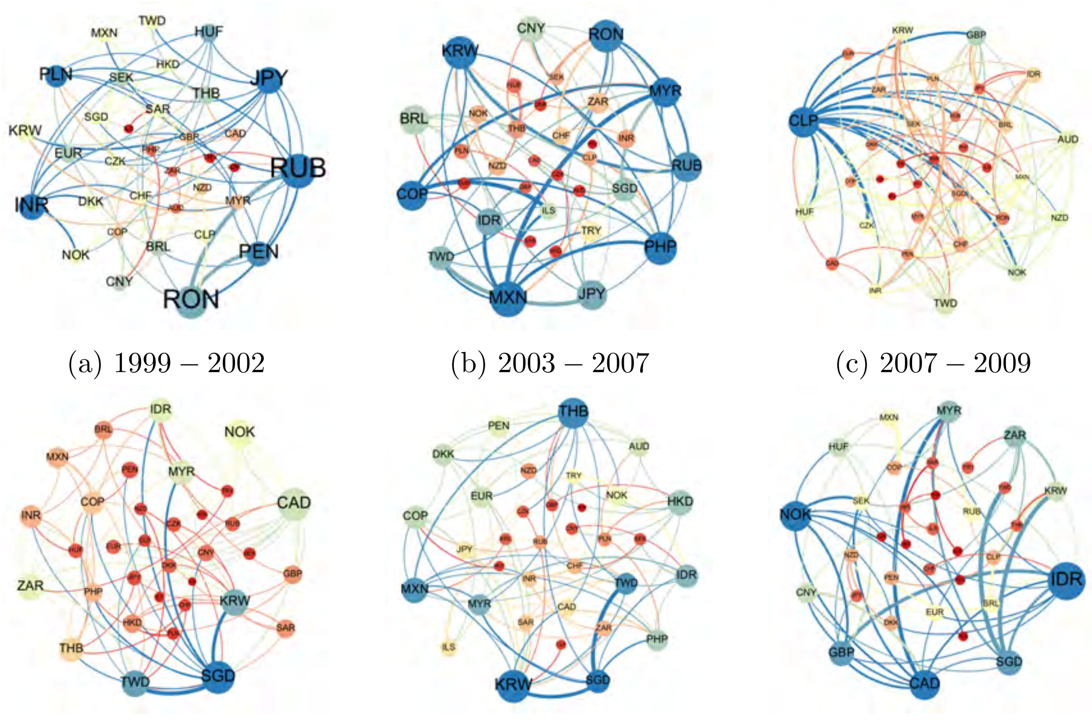
Figure 2: **Fitted distribution for Node degrees**

It can be observed from Figure 2 that distribution of weighted degrees has long right tail: nodes with degrees smaller than 0.03 account for the majority while nodes with degrees exceeding 0.05 are around 5% to 10%. Figure 2 seemingly shows that continuous power law distribution (red dashed line) does not fit the distribution of total weighted degree as good as log normal distribution. It tends to perform well if only degrees from around 0.018 are considered. However, goodness-of-fit test based on a bootstrap of 5000 iterations does not reject the hypothesis that observed data set actually follows a power law. Vuong's test, a likelihood ratio test for model selection using the Kullback-Leibler criteria (Gillespie, 2014), also fails to support log normal distribution over power law (p-value = 0.504) although the negative test statistics slightly favors the former. Tests on distribution of total degrees give similar conclusions (Table 4). We can, thus, safely say that total degrees of global currency network based on conditional granger causality have power law distribution. This finding agrees with other studies in foreign exchange market (Górski et al., 2008; Wang and Xie, 2016) but with unpopular alpha values compared to the 2 - 3 range documented in Newman (2005).

Table 4: Power Law distribution fit

		Degree	**Weighted Degree**
X-min	Mean	13.01	0.020
	Standard Deviation	2.76	0.004
Alpha	Mean	7.73	4.028
	Standard Deviation	3.00	1.471
Power law fit test	p-value	0.61	0.603
Vuong test	Test statistics	-0.65	-0.010
	p-value	0.74	0.504

Source: Author's calculation



(a) 1999 – 2002 (b) 2003 – 2007 (c) 2007 – 2009

(d) 2009 – 2012 (e) 2012 – 2015 (f) 2016 – 2017

Figure 3: **Networks of global currencies over sub-periods**

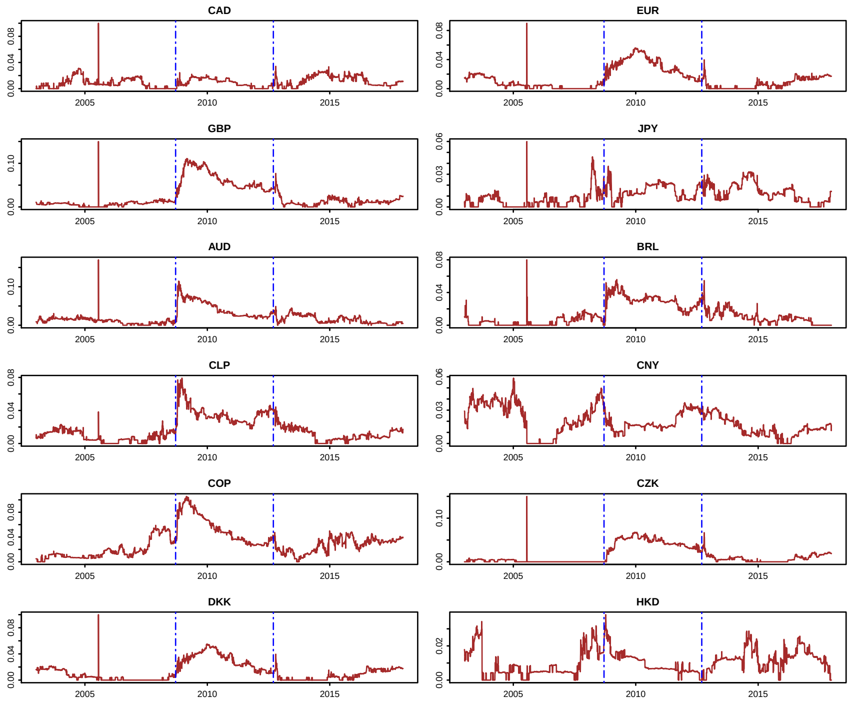
Table 5: **Dynamic communities of global currency networks**

1999/17	**1999/02**	**2003/07**	**2007/09**	**2009/12**	**2007/12**	**2012/15**	**2016/17**
BRL	MXN	RUB	CZK	JPY	JPY	THB	MYR
CLP	PHP	JPY	CAD	GBP	CNY	NOK	AUD
COP	CAD	TWD	EUR	CNY	THB	CZK	ILS
INR	GBP	KRW	CLP	CZK	EUR	MXN	CNY
IDR	CNY	AUD	TRY	CAD	DKK	MYR	INR
MXN	SGD	ZAR	INR	EUR	SEK	CNY	PHP
PEN	THB	HKD	DKK	DKK	NOK	IDR	CAD
PHP	INR	CZK	HUF	PLN	RON	TRY	NOK
TRY	HKD	CAD	PLN	SEK	AUD	PLN	CZK
CAD	EUR	SGD	RUB	NOK	IDR	HKD	EUR
GBP	DKK	MYR	JPY	HKD	TRY	GBP	DKK
JPY	HUF	PEN	GBP	SAR	NZD	RUB	NZD
AUD	NZD	MXN	IDR	RON	ILS	EUR	HUF
CNY	NOK	PHP	ILS	RUB	HUF	DKK	IDR
MYR	SEK	GBP	BRL	IDR	CZK	AUD	PLN
RUB	COP	EUR	CNY	BRL	PLN	NZD	GBP
SGD	IDR	COP	THB	TRY	CLP	ILS	RON
CHF	PEN	IDR	TWD	MYR	INR	HUF	JPY
TWD	RUB	SAR	AUD	CLP	PHP	COP	SEK
THB	SAR	ILS	SGD	TWD	MXN	PEN	MXN
HKD	ILS	BRL	MYR	SGD	COP	BRL	COP
SAR	RON	CLP	PHP	NZD	PEN	RON	PEN
ZAR	JPY	TRY	SEK	KRW	HKD	JPY	BRL
KRW	TWD	CNY	NZD	ZAR	SAR	SEK	TRY
EUR	KRW	THB	NOK	ILS	KRW	CLP	HKD
CZK	CZK	INR	MXN	THB	ZAR	KRW	RUB
DKK	BRL	DKK	COP	INR	GBP	TWD	SAR
HUF	CLP	SEK	PEN	HUF	CAD	SGD	CLP
ILS	TRY	RON	KRW	PHP	RUB	CHF	THB
NZD	AUD	CHF	ZAR	MXN	BRL	INR	ZAR
NOK	MYR	HUF	HKD	COP	MYR	PHP	KRW
PLN	CHF	NZD	SAR	PEN	TWD	SAR	TWD
RON	ZAR	NOK	RON	CHF	SGD	ZAR	SGD
SEK	PLN	PLN	CHF	AUD	CHF	CAD	CHF

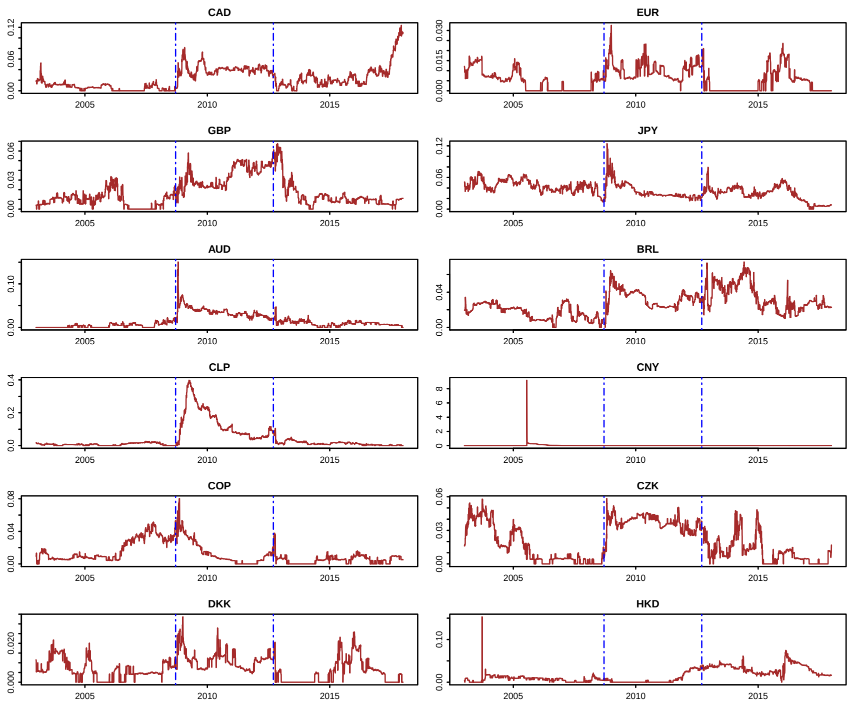
3.2.3. Connectedness structure

Community structure exists if the nodes of the network can be easily grouped into sets of nodes such that each set of nodes is densely connected internally. It is essential to notice that overlapping communities are also allowed. Results of community detection using Louvain algorithm are shown on Table 5. It is inherent that the number of communities as well as members within each community varied over time and from samples to samples. Nevertheless these communities share some similar characteristics. First, almost all of them are dominated by currencies having either similar geographical condition or similar level of development regarding economies that issue the currencies. Second, there are core or central members that connect the rest of each community. Take the sample of whole period 1999 - 2017 for instance. Table 5 reveals 4 communities are found based on conditional Granger-based weighted and directed network. The first community from the top left is typically Latin America- or EAGLES- dominated. Figure 1b clearly shows BRL, MXN and IDR are the three core nodes that tie members together in one group. Seven out of eleven currencies in community two are from advanced economies, namely CAD, GBP, JPY, AUD, SGD, CHF and TWD . To some extent, the community is Asia-dominated since more than half of it are from Asia and three out of four core currencies are Asian, including SGD, TWD and MYR (Figure 1b). By similar reasoning, we can argue that the third community is in fact Asia-dominated. The last community, however, is undoubtedly European as eight among nine of its members are currencies of European countries and Israel, which is geographically in between Europe and Asia. Furthermore, it is the three European currencies including NOK, CZK and RON that connect all members together. In short, there are reasonable economic and geographical reasoning behind each group of currencies. This finding is, thus, agree with and further confirms the results of previous studies (Ortega and Matesanz, 2006; Kwapień et al., 2009; Jang et al., 2011; Matesanz and Ortega, 2014).

Another interesting observation that can be drawn from Table 5 is: there exist groups and pairs of currencies that consistently fell within one community; and they can be in the same or different continents. Regarding Asian currencies, we have KRW/TWD/SGD, KRW/TWD/JPY, THB/CNY, TWD/SGD, JPY/TWD and KRW/TWD . For European currencies, we have somewhat bigger groups and more consistent pairs: NOK/SEK/DKK, NOK/SEK/PLN/CZK, NOK/SEK/PLN/DKK/CZK, NOK/SEK, HUF/PLN, SEK/DKK, CZK/PLN . Concerning Latin America, the pair COP/PEN is the most consistent over time and so is the the group COP/PEN/MXN . To a lesser extent, we have BRL/COP, BRL/CLP and the group BRL/COP/PEN. Consistent strong connections are not only found among currencies in the same region but also across regions as well. These include: GBP/CAD, TRY/BRL, TRY/CLP, SGD/CAD, AUD/MYR, TRY/BRL/CLP and CHF/TWD/SGD . These stable links can be formed thanks to international trade, investment or portfolio rebalancing among substitute currencies.



(a) From-others connectedness



(b) To-others connectedness

Figure 4: **Rolling To and From connectedness**

3.2.4. Rolling from-others and to-others connectedness

Rolling to-others connectedness reflect the effect of one currency on the system while from-others connectedness capture the opposite direction effects. Brown lines in Figure 4 show the dynamic rolling from- and to-connectedness of selected currencies (to save space). In each figure, the first vertical dashed blue line coincides with the collapse of Lehman Brothers on 15 September 2009, and the second one is on 12 September 2012 when the German Court approved the European Stability Mechanism. It can be seen that, these two events exerted considerable impacts on both series of connectedness: both see a spike in between the events. Another striking feature observed in Figure 4a is a big jump in mid 2005 in all series except for HKD. Similar phenomenon is observed in CNY's to-others rolling connectedness. It turns out these spikes occurred on 22 July 2005, one day after the People's Bank of China announced its policy shift from pegging to managed floating exchange rate. Given the potential growth of Chinese economy, its positive states of current and financial accounts and international reserves, CNY would appreciate against USD and other major currencies. Quick market responses make the outgoing connectedness of CNY to others rose from 0.0143 the previous day to an all time height of 9.2 on 22 July 2005, dropped back to 1.46 and 0.54 over the next two business days then stabilized around 0.39 to 04 August 2005. This big spillover then was absorbed by most other currencies. The mean from-other connectedness rose from 0.0113 to 0.28 from 21 to 22 July 2005, fell back to 0.054 on 25 July before sustained around 0.02 to mid August of the same year. The impacts from Chinese exchange rate policy, the Lehman Brothers' collapse and approval of European Stability Mechanism can also be seen on Figure 7 regarding total connectedness.

3.3. Group connectedness

3.3.1. Number of links

Apart from endogenously-formed groups in the previous section, another way to investigate the structure of connectedness is to see how the links are distributed among different groups of currencies. Based on the number of outward links, currencies from advanced economies are main spreaders of returns over the entire period 1999 - 2017 (Table 6). Table 7 reveals that more links are seen across groups than within each subgroups. In sub-periods from 2003 to 2015, most links originated from OTH while in the rest two sub-periods, G11 were the main originators. Links from OTH increased in the sub-prime credit crisis while links from G11 increased in the latest sub-period. It can also be observed that, most connections are related to emerging economies. Indeed, the percentage of links that have currencies from emerging economies as one end is averagely 78.1% in medium term (average of sub-periods) and 76.6% in long term (1999-2017). The same ratios for advanced economies' currencies are 58.1% and 67.9% relatively. Over the long run, there are more EAGLES-related connections (51.5%) than connections related to all other sub-groups. Table 7 also shows that connections within emerging and within advanced groups are more dense than across these two broad groups, accounting for 55.5% total connections in 1999-2017. Higher intra-group connectedness is also seen in EAGLES: the ratios of total links between

EAGLES per total links from EAGLES were highest during 2003 - 2007 at 67.44% then fluctuated around 55% from 2007 to 2015. On the relationship between one subgroup to another, in the long run, more links are found between EAGLES and OTH (16.3%) but in short to medium term, links between EAGLES and G11 (12.03%) are slightly more than between any other subgroups.

3.3.2. Net to-others connectedness

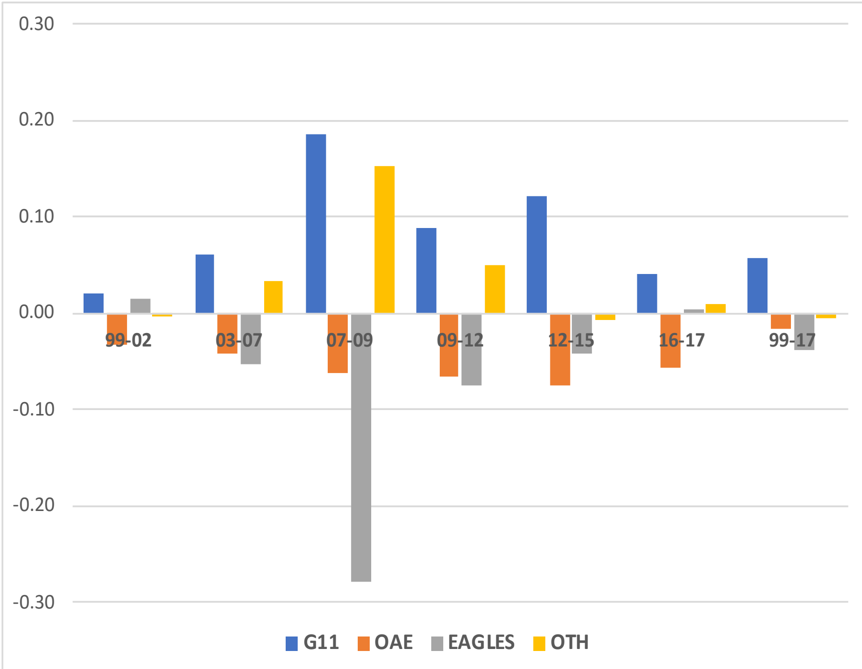


Figure 5: **Net connectedness among currency groups**

Figure 5 shows the dynamics of net connectedness among the four currency blocs G11, OAE, EAGLES and OTH over time. Net to-others connectedness of a particular bloc is the difference between to-others connectedness and from-others connectedness. Different from connectedness of a node, bloc connectedness is measured using MVGC framework, which, according to Barnett and Seth (2014), already accounts for intra-group connections. Net connectedness in this case, is net return spillover, reflecting whether a group is a net receiver or transmitter of change in exchange rates. Figure 5 reveals several interesting information. Firstly, the magnitude of spillovers vary through time, highest in 2007-2009 and lowest in 1999-2002. Secondly, the bloc of major currencies G11 plays as net transmitter while EAGLES and OAE are net receivers. Changes in values of EAGLES's currencies were driven the most by changes in other blocs while changes values of G11 currencies exerted highest impact on others, especially during the two crises. Regarding OTH bloc, overall spillover this bloc received balanced with what they spread out. Nevertheless the bloc was net spillover over sub-periods from 2003 to 2012, with highest magnitude seen in 2007-2009. Given generally higher interest for this group, literature suggests that carry trade activities may have a say (Melvin and Taylor, 2009; Kohler, 2010).

Table 6: **Pair-wise G-causality connection among groups of currencies**

Relationship	99-02		03-07		07-09		09-12		12-15		16-17		99-17	
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
G11 — G11	4	7.1	2	2.2	12	7.9	11	11.1	7	6.0	11	17.2	16	8.7
G11 — EAGLES	6	10.7	4	4.3	18	11.8	5	5.1	6	5.1	7	10.9	16	8.7
G11 — OAE	5	8.9	3	3.2	6	3.9	9	9.1	9	7.7	3	4.7	11	6.0
G11 — OTH	5	8.9	6	6.5	2	1.3	4	4.0	6	5.1	4	6.3	10	5.4
From G11 to the rest	*16*	*28.6*	*13*	*14.0*	*26*	*17.1*	*18*	*18.2*	*21*	*17.9*	*14*	*21.9*	*37*	*20.1*
From G11	***20***	***35.7***	***15***	***16.1***	***38***	***25.0***	***29***	***29.3***	***28***	***23.9***	***25***	***39.1***	***53***	***28.8***
OAE — OAE	1	1.8	2	2.2	4	2.6	4	4.0	5	4.3	2	3.1	5	2.7
OAE — G11	3	5.4	1	1.1	9	5.9	1	1.0	5	4.3	0	0.0	11	6.0
OAE — EAGLES	0	0.0	6	6.5	5	3.3	7	7.1	7	6.0	5	7.8	14	7.6
OAE — OTH	1	1.8	0	0.0	3	2.0	4	4.0	4	3.4	1	1.6	15	8.2
From OAE to the rest	*4*	*7.1*	*7*	*7.5*	*17*	*11.2*	*12*	*12.1*	*16*	*13.7*	*6*	*9.4*	*40*	*21.7*
From OAE	***5***	***8.9***	***9***	***9.7***	***21***	***13.8***	***16***	***16.2***	***21***	***17.9***	***8***	***12.5***	***45***	***24.5***
EAGLES — EAGLES	3	5.4	15	16.1	6	3.9	12	12.1	11	9.4	8	12.5	19	10.3
EAGLES — G11	6	10.7	3	3.2	1	0.7	1	1.0	1	0.9	5	7.8	4	2.2
EAGLES — OTH	7	12.5	2	2.2	3	2.0	2	2.0	1	0.9	3	4.7	13	7.1
EAGLES — OAE	2	3.6	6	6.5	3	2.0	4	4.0	3	2.6	2	3.1	11	6.0
From EAGLES to the rest	*15*	*26.8*	*11*	*11.8*	*7*	*4.6*	*7*	*7.1*	*5*	*4.3*	*10*	*15.6*	*28*	*15.2*
From EAGLES	***18***	***32.1***	***26***	***28.0***	***13***	***8.6***	***19***	***19.2***	***16***	***13.7***	***18***	***28.1***	***47***	***25.5***
OTH — OTH	2	3.6	29	31.2	44	28.9	19	19.2	29	24.8	4	6.3	10	5.4
OTH — G11	6	10.7	2	2.2	20	13.2	0	0.0	7	6.0	3	4.7	3	1.6
OTH — OAE	1	1.8	3	3.2	10	6.6	6	6.1	6	5.1	3	4.7	9	4.9
OTH — EAGLES	4	7.1	9	9.7	6	3.9	10	10.1	10	8.5	3	4.7	17	9.2
From OTH to the rest	*11*	*19.6*	*14*	*15.1*	*36*	*23.7*	*16*	*16.2*	*23*	*19.7*	*9*	*14.1*	*29*	*15.8*
From OTH	***13***	***23.2***	***43***	***46.2***	***80***	***52.6***	***35***	***35.4***	***52***	***44.4***	***13***	***20.3***	***39***	***21.2***
TOTAL	**56**	**100.0**	**93**	**100.0**	**152**	**100.0**	**99**	**100.0**	**117**	**100.0**	**64**	**100.0**	**184**	**100.0**

Table 7: **Further decomposition of pair-wise G-causality connection among groups of currencies**

Relationship	**99-02**		**03-07**		**07-09**		**09-12**		**12-15**		**16-17**		**99-17**	
	No.	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**	**No.**	**%**
G11 related	35	62.5	21	22.6	68	44.7	31	31.3	41	35.0	33	51.6	71	38.6
OAE related	13	23.2	21	22.6	40	26.3	35	35.4	39	33.3	16	25.0	76	41.3
EAGLES related	28	50.0	45	48.4	42	27.6	41	41.4	39	33.3	33	51.6	94	51.1
OTH related	26	46.4	51	54.8	88	57.9	45	45.5	63	53.8	21	32.8	77	41.8
Advanced related	40	71.4	38	40.9	93	61.2	56	56.6	66	56.4	46	71.9	125	67.9
Emerging related	43	76.8	85	91.4	121	79.6	74	74.7	91	77.8	48	75.0	141	76.6
Within Advanced	13	23.2	8	8.6	31	20.4	25	25.3	26	22.2	16	25.0	43	23.4
Within Emerging	16	28.6	55	59.1	59	38.8	43	43.4	51	43.6	18	28.1	59	32.1
Between Advanced - Emerging	27	48.2	30	32.3	62	40.8	31	31.3	40	34.2	30	46.9	82	44.6
Between G11 - EAGLES	12	21.4	7	7.5	19	12.5	6	6.1	7	6.0	12	18.8	20	10.9
Between G11 - OAE	5	8.9	7	7.5	12	7.9	5	5.1	8	6.8	2	3.1	22	12.0
Between G11 - OTH	11	19.6	8	8.6	22	14.5	4	4.0	13	11.1	7	10.9	13	7.1
Between OAE - EAGLES	2	3.6	12	12.9	8	5.3	11	11.1	10	8.5	7	10.9	25	13.6
Between OAE - OTH	2	3.6	3	3.2	13	8.6	10	10.1	10	8.5	4	6.3	24	13.0
Between EAGLES - OTH	11	19.6	11	11.8	9	5.9	12	12.1	11	9.4	6	9.4	30	16.3
Intra-groups	10	17.9	48	51.6	66	43.4	46	46.5	52	44.4	25	39.1	50	27.2
TOTAL	**53**	**94.6**	**96**	**103.2**	**149**	**98.0**	**94**	**94.9**	**111**	**94.9**	**63**	**98.4**	**184**	**100**

3.4. System-wide connectedness

3.4.1. Network connectedness over sub-samples

As put forward by Billio et al. (2012), network density reflects the global connectedness among assets or institutions and is measured by the ratio of realized edges per total number of possible edges. We call this the breath dimension of connectedness and introduce another dimension, namely depth connectedness, calculated by average weighted degrees of nodes. While the breath dimension tends to capture the quantity of linkages, the depth dimension reflects the strength of connection between nodes.

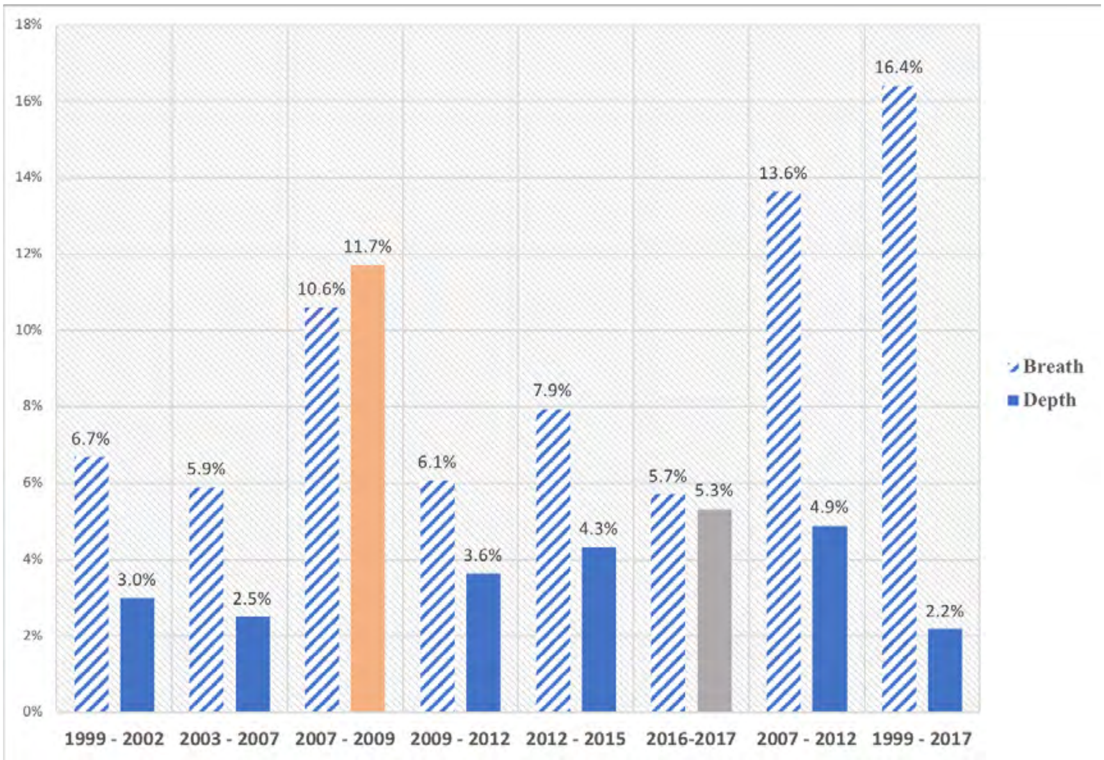


Figure 6: **Snapshots of Network Total Connectedness**

Figure 6 and Figure 3 show network connectedness over the study period 1999 - 2016, subdivided into six short periods. It seems that breath connectedness is very sensitive period's length whereas the depth connectedness is not. Though covering less time span, depth connectedness of the double crisis period are higher than the whole period. This phenomenon is easily seen in the global financial crisis period 2007 - 2009, when a big spike in connectedness is witnessed, especially in the depth. This reflects the fact that the sub-prime credit exert a huge impact on the connectedness, boosted both the number of connections and the strength of connections in the global foreign exchange. Lower connection's density and strength in 2009 - 2012 as compared to 2007 - 2009 may reflect the fact that the surprising or unexpected factors may have dropped. The higher in both dimensions of 2012 - 2015 compared to 2009 - 2012 is potentially due to longer time span but could capture the ups and downs in this period due to: oil price fluctuation, instability in Europe. Noticeably the connectedness strength in 2016-2017 is second highest only after that of the great depression period, well reflecting the uncertainty over the last two years created by Brexit and triumph of populism in the United States and rising populism in several countries in Europe. Our depth dimension of connectedness thus help to adequately capture the effects of systemic events and better identify chaotic and uncertain periods. These can be seen more clearly with three year rolling connectedness.

3.4.2. Rolling network connectedness

Figure 7 visualizes the relationship between rolling connectedness, total number of links with two systemic events (top left and bottom left), the two consecutive crises (top right) and three recent recessions in OECD economies (bottom right). Information about the series is provided on Table 8. On average, the Granger-based currency network has 93 edges, with average density of 8.3% and average strength per node of 0.04. Only 1% of cases the density went down below 4.3% or above 16.8% corresponding to 48 and 188 edges relatively. The max density is 18.2% reached one month after the Lehman Brothers' event, when the total number of links were 204. On the other hand, max level of average strength did not fall on the crisis period but nearly coincided with the exchange rate policy shift of China, when all time height of 0.56 was achieved. However, the lowest levels of both series were in 2005 and 2006 while the their average highest were in the last quarter of 2008.

Table 8: **Basic statistics of Rolling Connectedness**

	Mean	**Max**	**Min**	**1%**	**5%**	**95%**	**99%**
Density (%)	8.3	18.2	3.8	4.3	4.8	16.0	16.8
Number of Links	94	204	43	48	54	179	188
Average Strength	0.04	0.56	0.02	0.02	0.02	0.09	0.09

Two sub-figures on the left of Figure 7 are relatively the rolling breath connectedness (on top) and rolling depth connectedness (at bottom). With exception of two extreme peaks in July 2005 and October 2012 of depth connectedness, the two dimensions nearly vary in tandem, with similar patterns observed over time. Interestingly, these two series have captured well different important event over the given period. In fact, there is a surge in both series on 22 July 2005, one day after People's Bank of China announced the switch from pegged to managed floating exchange rate regime. Spikes are also seen not long after the fall of Lehman Brothers as well as the approval of German court for European Stability Mechanism. While the former event marked the outbreak of the global financial crisis, the latter paved way to the end of European Sovereign Credit problem. The series did not fall immediately after the court got-through is understandable: there is time for finalizing the mechanism and more importantly markets need time to react to news in chaotic situation. Here, we have to note again that, the breath dimension of connectedness, though less volatile, does not capture the magnitude of the impact of events like Chinese exchange rate policy shift or the establishment of European Stability Mechanism. As for this, our depth dimension does a better job.

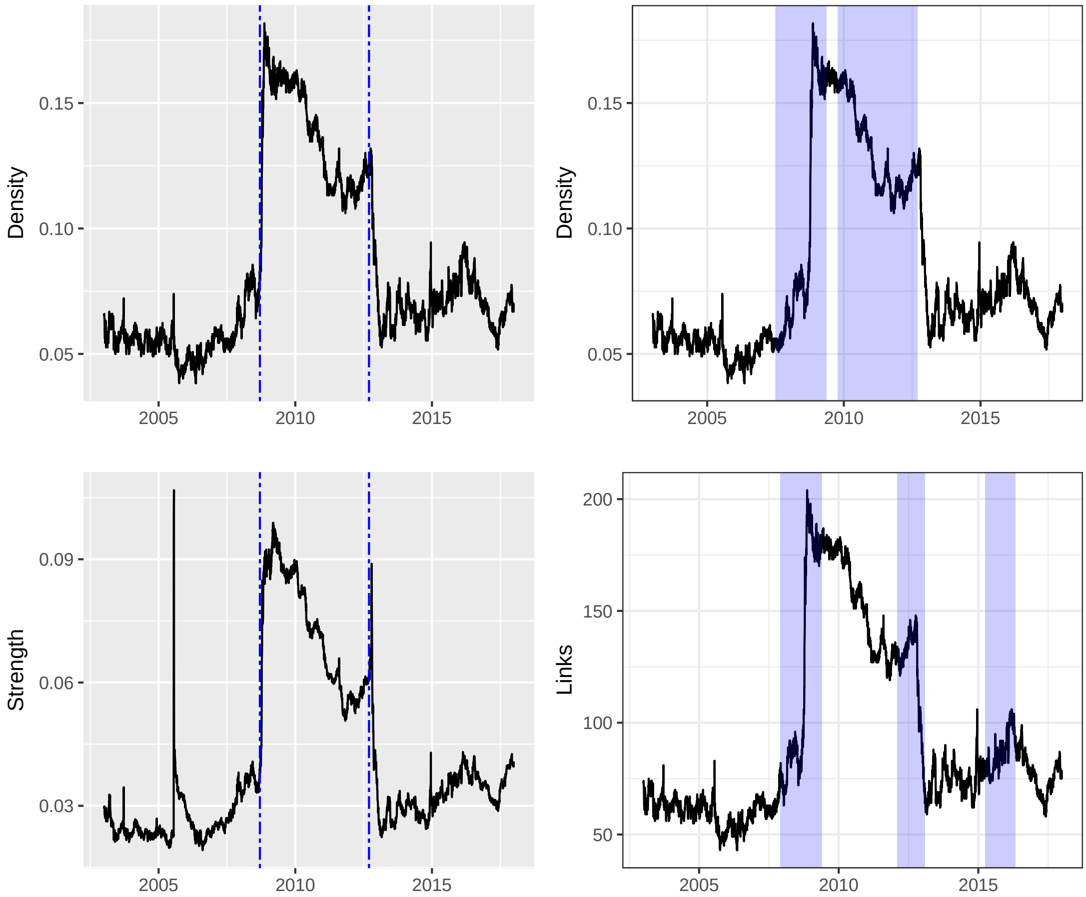


Figure 7: Connectedness, Systemic Events, crises, recessions

Clearly, the period of September 2008 to September 2012 can be considered the peak of two consecutive crises and thus global financial markets were in a period of high uncertainty. The sustaining high level of density and average strength captures this fact. Two sub-figures on the right panel also reveal that the rolling connectedness is informative about the crises and recession periods. Peaks in the series fall within each identified recession period for OECD countries. According to Melvin and Taylor (2009), the crisis in foreign exchange derived from subprime credit crisis and stock markets' turbulence and thus came relatively late. According to these authors, foreign exchange market crisis is closely related to carry trade, which is a very popular strategy for currency investors. It involves buying high interest currencies, funded by sellling low interest rate currencies, thus profiting via interest rate differences. This strategy has its root in the observation that interest rate parity (IRP) does not always work. IRP suggests that the difference in interest rates will be offset by the appreciation of low-interest currencies over high-interest currencies but in reality the high interest currency tend to appreciate against the low interest currencies (Melvin and Taylor, 2009; Kohler, 2010). Carry trade is obviously risky, and thus often unwinded during market stress. From the view of practitioners, the proposed a crisis time-line with four important months, making four legs of the foreign exchange crisis, namely

Figure 8: Depth connectedness from 2007 to 2008

August 2007 - Contagion from other assets, November 2007 - Credit, commodities and deleveraging, March 2008 - Bear Stern and illiquidity and lastly September 2008 - Lehman Brothers and counter-party risks. In the first leg contagion from bond and stock markets lead to a major unwinding of the carry trade and caused huge losses to many currency investors. The second leg was marked by an abrupt carry trade return fall in early November 2007 and mainly concerned with borrowing difficulty, falling commodity prices and wide-spread deleveraging across investment funds. It turns out that the rolling depth connectedness can reflect well these events. Figure 8 reveals an upward trend in the series with minor increase in August compared to July 2007 (averagely from 0.027 to 0.028), a more visible rise in November 2007 compared to previous months. The series rises again from March 2008 then hardly crosses 0.04 and tends to go down until August 2008. However, it begins to rise steeply in September accompanied by a sudden jump in October 2008 when the connection strength nearly doubled from 0.044 to 0.084 within 12 days, from 06/10/2008 to 17/10/2008. Does this reflect the risk behaviors in real world? According to Melvin and Taylor (2009), after orderly takeover of Bear Sterns by JP Morgan Chase, the 'too big too fail' issue was consolidated, market fears were calmed down and many thought that the world was once again returning to normal in early second quarter of 2008. The sudden jump in the series occurs within three weeks after Lehman declared bankruptcy. Seemingly, the more significant the incident, the higher the strength (as well as density). The behaviour of rolling connectedness, thus, matches well with the foreign exchange crisis process and episodes described in Melvin and Taylor (2009) and better captures the dynamics in foreign exchange market from 2007 to 2008 than total connectedness in Diebold and Yilmaz (2015).

It can be seen that not only the number of connection by also the strength of connection rises and maintains at a high level during stock market turmoil period. This confirms the close relationship between equities and foreign exchange rates

(Cho et al., 2016; Atanasov and Nitschka, 2015) in the context of increasing cross-border investment. This also points to the fact that assets returns are more connected in bearish market as compared to normal or bullish (da Silva Filho et al., 2012). In an informally efficient FX market, short-term exchange rate changes should not be related to other lagged exchange rates. Thus, one possible explanation for the 4 year sustaining high level of connectedness: after Lehman Brother event to October 2012 is the period of high uncertainty, low risk tolerance and the market is highly informationally inefficient. Good reasons for the effect of uncertainty and risks on connectedness can be found in Billio et al. (2012):

> "...in the presence of value-at-risk constraints or other market frictions such as transaction costs, borrowing constraints, costs of gathering and processing information, and institutional restrictions on short-sales, we may find Granger causality among price changes of financial assets. Moreover, this type of predictability may not easily be arbitraged away precisely because of the presence of such frictions."

The work of Kohler (2010) offers a more practical explanation for a long period of sustained high connections in currency market besides market efficiency issue. Kohler compared the global financial crisis 2007-2009 with the Asian financial crisis of 1997-1998 and the Russian debt default in August 1998 and noted that previous two crises occurred in emerging economies while the most recent in the most developed country with safe-haven currency. Thus, although all three crises lead to substantial movements in exchange rates, instead of depreciating, USD strongly appreciated against most other currencies at the heart of the crisis and then strongly reversed after that. Flight to quality and flight to liquidity paved way for capital moving into safe haven currencies like USD, leading to strong appreciation against most others. After a short time, reversal in risk aversion and carry trade activities made capital flows in reversal direction, leading to appreciation of other currencies against USD. Kohler (2010) found that in the latest financial crisis, interest rate differences, and thus carry trade, had much more profound effects on exchange rate movement than in the two previous ones. This is reasonable when policy interest rates of major economies including Great Britain, Japan, Euro zone and the United States dropped significantly to lowest levels (in between 0% and 1%) in response to the Lehman Brothers' collapse (Fawley et al., 2013). Lim and Mohapatra (2016) document that after a sudden halt following Lehman's fall, from mid-2009 to March 2013, cumulative quarterly gross financial inflows into developing economies increased 211% from $USD192$ billion to $USD598$ billion. We, therefore, suppose that it was these massive inflows and out-flows of capital that lead to high correlation in exchange rates, given all having USD as the base currency. Together with constraints addressed by Billio et al. (2012), profit opportunities from significant lead-lag relations could not be exploited, thus Granger-caused connectedness remained high. The connectedness should have dropped further after mid - 2009 when positive stress test results of US banks came out if European public debt problems did not emerge (Diebold and Yilmaz, 2015). The sovereign debt crisis threatened the stability of European Union and exerted strong impacts on the common currency EUR, and thus prolonged the uncertainty situation in global financial markets, especially bonds and foreign exchange markets. However, as the surprising factors gradually lost ground, herd behaviours were not as strong as in previous crisis, connections gradually dropped. Efforts from European Central Bank (ECB) and European governments step by step reduced risks but only when the feasibility of European Stability Mechanism fully appreciated by the market, did connectedness structurally fall.

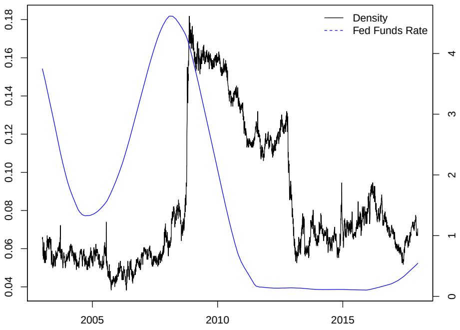
3.5 Rolling total breath connectedness and major economic and financial indicators

In previous sections ,we found that rolling connectedness captures well systemic events, fits well with crises and recessions. The question is then, is there a good relationship between rolling connectedness and major economic indicators? To answer this, we plot the series against TED spread, fed funds rates and Volatility Index (VIX) and examine correlation correlations between them. The TED spread is commonly a proxy for funding liquidity and credit risk in the interbank market. It is the difference between the three-month US. LIBOR and the three-month US Treasury bill rate. The volatility index, VIX is a popular measure of the stock market's expectation of volatility implied by S&P 500 index options. It is widely picked as a proxy for market fear and uncertainty. We also compare currency market connectedness with VSTOXX, which has the same economic meaning as VIX but applied for European stock market. Fed Funds rate is often considered as a gauge of the cyclical position of the U.S economy.

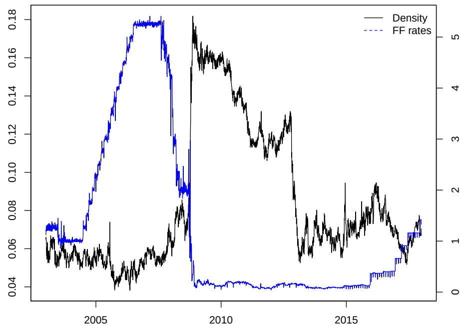
Table 9: **Correlation between density and major economic indicators**

Indicators		**1999/17**	**2007/09**	**2007/12**	**2016/17**
Level	VIX	0.60	0.83	0.33	0.56
	TED	0.09	0.11	-0.37	0.08
	FFR	-0.52	-0.88	-0.82	-0.59
	VSTOXX	0.55	0.82	0.37	0.64
Rolling mean	VIX	0.45	0.92	0.56	0.61
	TED	0.88	0.92	0.88	-0.73
	FFR	-0.01	-0.80	-0.34	-0.52
	VSTOXX	0.17	0.91	0.49	0.53

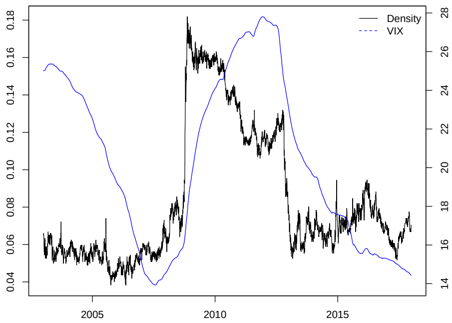
Relationship between rolling connectedness and three major economic and financial indicators is reflected on Table 9 and Figure 9. Three sub-figures on the left show the dynamics of density with 4 year rolling mean of the three indicators while sub-figures on the right-hand side depicts the relationships in levels. We use four years for the rolling window as the connectedness is also computed on 4-year window basis. The series in level provide short-run information while the 4-year rolling mean implies medium term. Some important features are revealed. First, rolling connectedness is counter-cycle since it is highly negatively correlated with the Fed Funds rate while highly positively correlated with risk indicators like TED spread, VIX and VSTOXX. In general, rolling density fell



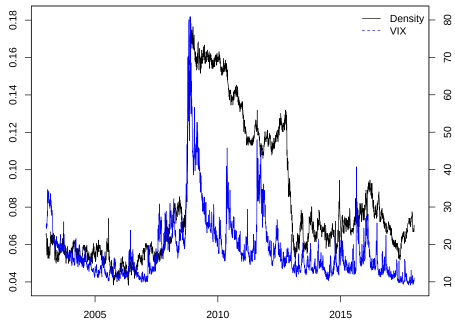
(a) Density and Rolling FF rate



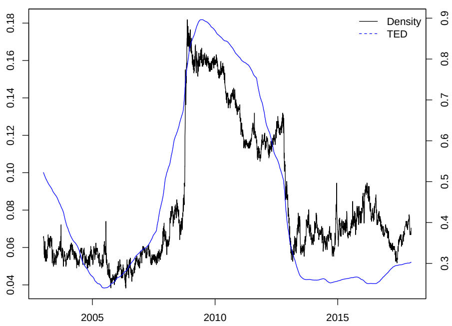
(b) Density and FF rate



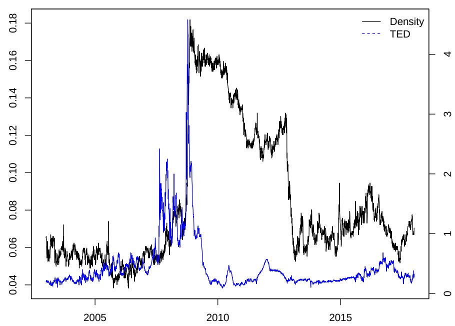
(c) Density and Rolling VIX



(d) Density and VIX



(e) Density and Rolling TED

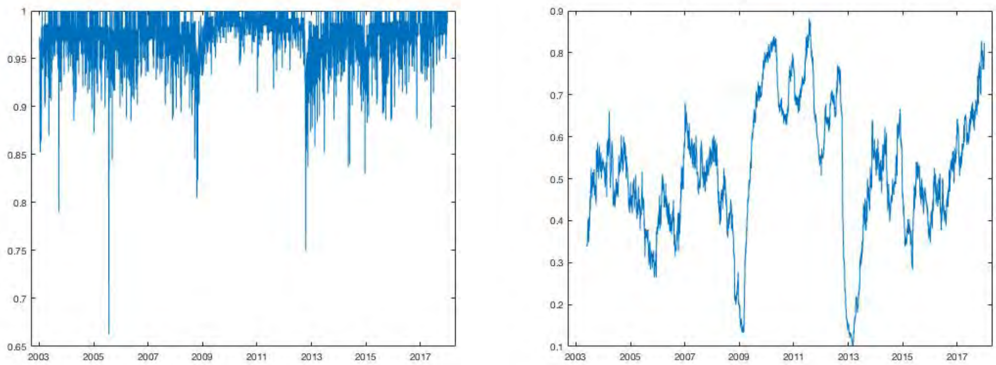


(f) Density and TED

Figure 9: **Rolling connectedness and major economic and financial indicators**

when FF rate rose and vice versa (Figure 9b), rose and spiked together with VIX (Figure 9d) and TED, especially during crisis period (Figures 9e and 9f). In fact, its correlations with all risk series rose dramatically in the global financial crisis 2007-2009 (Table 9. This is contrary to Diebold and Yilmaz (2015) who argue that total volatility connectedness is not counter-cyclical. Second, high association of currency connectedness both with VIX and Ted spread in the global financial crisis reflects the fact that: fears, credit risk and liquidity risk were also prevailing in foreign exchange market at that time. Correlation with VIX is higher than with VSTOXX over the whole period as well as in the first crisis possibly mean that overall the series better capture expected fear and uncertainty in US market. However, higher correlation with VSTOXX than with VIX during 2007-2012 and 2016-2017 indicates that our currency connectedness captures very well volatility in European stock markets during these periods of time. Third, rolling connectedness potentially conveys contemporary information about stock market fear while reflects medium to long term trend of credit and liquidity risk, with exception of 2016-2017 period. Our main findings here agree with Greenwood-Nimmo et al. (2016) though our approach is much simpler. Thus, in light of Billio et al. (2012), rolling connectedness can potentially be an indicator of systemic risk. From Figure 7, we suggest that if density drops down below its 5% quantile, a period called 'silence before a storm' may be created. On the other hand, when density exceeds the seemingly 'resistance level' 10%, it may signify the widespread or end of bad period of time.

3.6. Network connectedness stability



(a) Single step survival ratio (b) 100-step survival ratio

Figure 10: **Single and multi-step survival ratio**

On average after one single step, 97.24% of links previously formed remains while the ratio is 65.11% for 50 steps and 51.67% for 100 steps. This seemingly means that the connectedness is fairly stable, it does not fall under 50% after 100 steps on average. Nevertheless Figure 10 shows that the stability is highly time-dependent. The single step ratio fell down to 65 - 70% round the mid 2005, to 80% in the first month of 2009 and to 70% near the end of 2012. The 100-step survival ratio also see a plunge in early 2009 and late 2012 to nearly 10%. Both

Figure 10a and Figure 10b shows a highly stable connection in between 2009 and 2012. They also show steady increase in connection stability to the end of 2017, further confirming the fact that cross-over spillovers increase and remain high during high uncertain periods when market mispricing cannot be quickly exploited.

3.7. Robust studies on rolling total connectedness

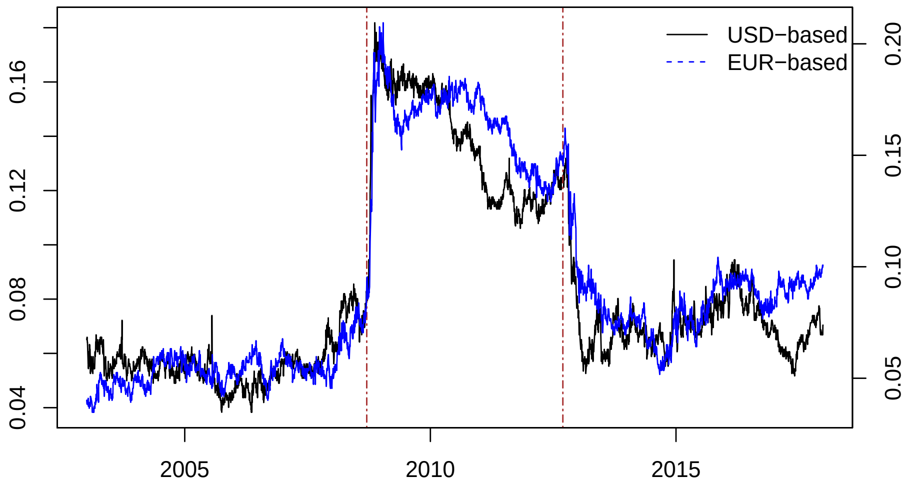


Figure 11: **Connectedness with EUR as the base currency**

First, to check whether the base currency affect the result or not we performed the same techniques over EUR-based series. EUR-based rolling connectedness has higher average value. It shows a stronger inclination towards EUR-related problematic times with higher values in sovereign debt crisis and around Brexit. However, Figure 11 exhibits that the two series possess similar pattern over time. Specifically, both shows sustained all-time high levels in between the two crises; and important structural changes found around the two systemic events above-mentioned.

Second, following suggestions in Billio et al. (2012), we first adjust each return series for GARCH effects by dividing it by the conditional standard deviation obtained from GARCH(1,1) then perform conditional Granger causality analysis on the adjusted series. Specifically, the conditional standard deviation series are obtained from the following baseline model of returns:

$$R_t^i = \mu_i + \sigma_{it}\epsilon_t^i, \epsilon_t^i \sim WN(0,1)$$

$$\sigma_{it}^2 = \omega_i + \alpha_i(R_{t-1} - \mu_i)^2 + \beta_i\sigma_{it-1}^2 \tag{25}$$

This procedure yields less linkages, and has basically different pattern (Figure 12. Density sees a structural break from September 2008 but climbs to higher levels

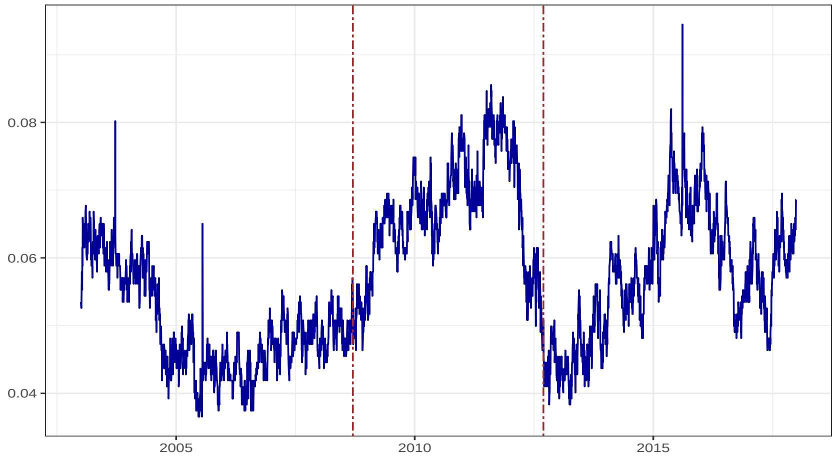
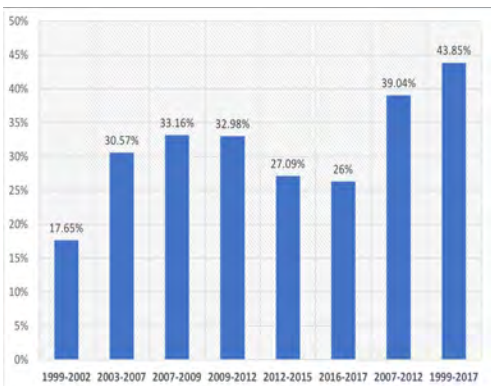


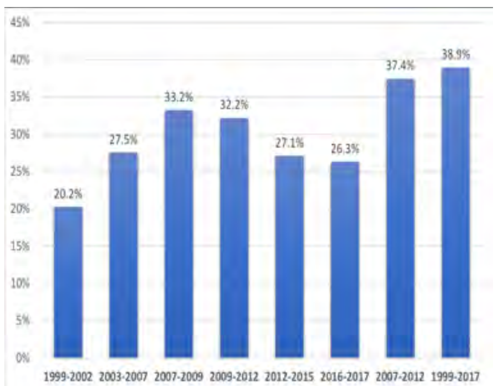
Figure 12: **GARCH - adjusted rolling density**

during the European public debt turmoil. It begins to drop long before September 2012, then reaches highest level around October 2015, within the recession period 2005-2006.

Third, we adopt bivariate non-conditional granger-causality methods to see whether the results regarding breath connectedness change or not. Final results are presented in Figure 13. It can be seen that, results with raw log returns and GARCH-adjusted returns make virtually no difference. Overall, the total number of links is nearly twice as much as that obtained from our method. This is understandable because bivariate G-causality does not take into account the effects of other. Regarding connectedness pattern, the density is highest during the global financial crisis but not very much higher than that in the economic expansion time 2003-2007 (33.16% compared to 30.57%) and only slightly higher than density of 2009-2012 (33.16% versus 32.98%). This is strikingly different from ours. Connectedness based on conditional G-causality, thus, is more informative.



(a) With raw log returns



(b) With GARCH-adjusted returns

Figure 13: **B**ivariate Granger-based network connectedness

Finally, the relationship between exchange rates are not entirely linear (Bekiros and Diks, 2008), we therefore conduct non-linear granger causality to supplement and confirm whether our linear model adequately capture the spillovers in higher moments or not. In this sense, we opt for Kernel method developed by Marinazzo et al. (2008a,b) because the authors' approach to test for granger causality is similar to ours. Both aim for conditional causality and both have stance in Granger (1969) when focusing on testing the significance of prediction error though the strategies to obtain degree of g-causality are not the same. Readers can refer to the work of these authors for details. In this framework, the inhomogeneous polynomial kernel with lag = 1 for VAR and model order d = 2 is used. As compared to Figure 7, Figure 14 indicates the existence of several non-linear relationships among the exchange rates. Indeed, the max, mean and median density obtained from non-linear G-causality are all higher than those from linear relationship. The number of links rose substantially after September 2008, sustained highest levels from 2009 to mid 2010, dropped significantly in 2011 then climbed up and fluctuated around 10% before and after the get-through of Financial Stability Scheme. Similar to the GARCH-adjusted series, the non-linear G-causality connectedness witnesses a hike in mid-2015, at a higher level than the peak in early 2013.

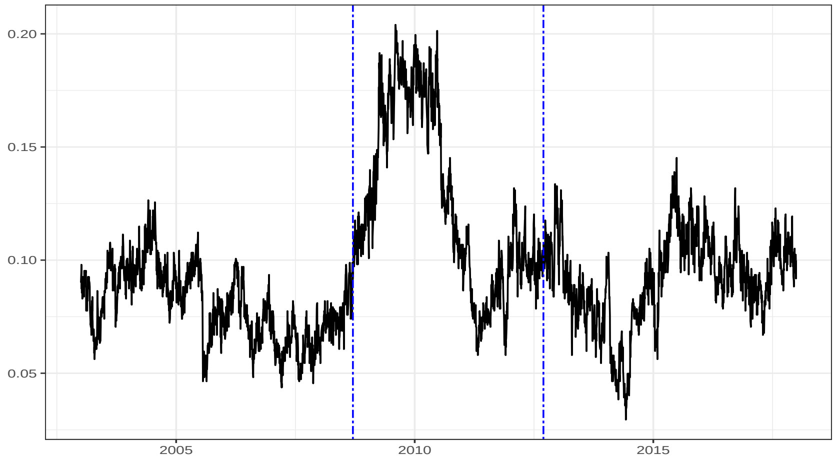


Figure 14: **Non-linear Granger causality network connectedness**

In summary, rolling connectedness using exchange rates against EUR yields similar result while connectedness series based on different techniques agree on one point: they all rise in crisis or recession periods. Nevertheless, non-linear connectedness, GARCH-adjusted connectedness and connectedness based on bivariate G-causality do not reflect the impacts of different systemic events as well as the original connectedness series. Figure 15 provides one way to track the development of systemic risk based on the behavior of this series over time. The red and blue dash-lines are relatively mean and median of rolling density in between 1999 and 2017. When density is below its median, global systemic risk is by and large low. Rolling density sustains above the blue line but below the red line could indicate higher systemic risk. Systemically above-the-mean values are usually associated with periods of high contagion risk or even crisis.

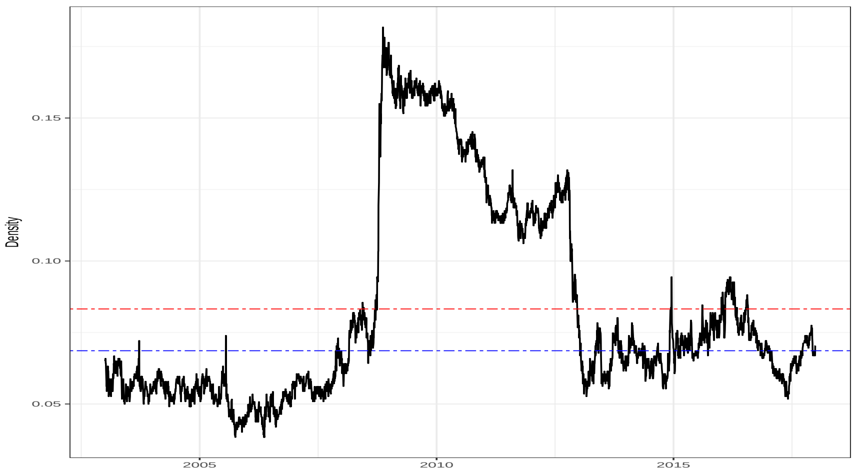


Figure 15: **Foreign exchange connectedness and systemic risk development**

4. Conclusion and future research

The purpose of this study is to investigate the dynamics of the global currency network connectedness. To achieve this, we rely on the concept network connectedness in Diebold and Yilmaz (2015) and Billio et al. (2012) and enhance their measurement approach using conditional granger causality from Barnett and Seth (2014) and Barrett et al. (2010). We first employed pairwise conditional granger causality to construct a weighted directed network based on 34 exchange rates of most traded currencies vis--vis USD and examine connectedness over time on three scales, including node-wise, group-wise and system-wise. Global currency network exhibited dynamics over the last nineteen years, when no currency is uniquely most central. We found that the top highest currencies are usually either currencies from advanced economies or from emerging and leading growth economies (EAGLES). Among G11 currencies, NOK and CAD were the most connected and influential. This is reasonable since Norway is neighbor of the Euro zone when Canada borders with the United States. Furthermore, these are net exporters of oil, which obviously exerted important impacts on the world economy over the last 15 years. The global currencies were structured into different communities depending on the number of links and more importantly, the strength of linkage among them. All communities have cores, with are highly and strongly connected. Though time-varying, several pairs and groups of currencies are repeatedly organized into one community in different sub-periods. This finding is beneficial for portfolio diversification, portfolio rebanlancing and pair trading. The rolling to- and from-connectedness as well as total breath and depth connectedness among these exchange rates varied in accordance with global risks and could capture major systemic events over the research period. The behaviour of rolling connectedness matches well with different crisis periods in foreign exchange market pointed out by Melvin and Taylor (2009). Furthermore, rolling total connectedness is counter-cycle, negatively correlated with fed funds rate and positively correlated with all risk indicators. With these properties, our proposed measurement of connectedness based on conditional granger causality complement those of Billio et al. (2012) and Diebold and Yilmaz (2015) and should be considered as an indicator of systemic risk. Policy makers can design real-time global currency connectedness index based on this result to gauge the development of systemic risk, at least to confirm with risk development else where. Future research should quantify the relationship between the centrality positions and risks as well as returns of exchange rates. Another direction is to identify the determinants of total rolling connectedness as well as whether or not this series can predict chaos in currency markets as well as stock markets.

Acknowledgement

References

Allen, F., Gale, D., 2000. Financial contagion. Journal of political economy 108, 1–33.

Anderson, R., Moore, T., 2006. The economics of information security. Science 314, 610–613.

Apostolakis, G., Papadopoulos, A.P., 2015. Financial stress spillovers across the banking, securities and foreign exchange markets. Journal of Financial Stability 19, 1–21.

Atanasov, V., Nitschka, T., 2015. Foreign currency returns and systematic risks. Journal of Financial and Quantitative Analysis 50, 231–250.

Barabási, A.L., Albert, R., 1999. Emergence of scaling in random networks. science 286, 509–512.

Barnett, L., Bossomaier, T., 2012. Transfer entropy as a log-likelihood ratio. Physical review letters 109, 138105.

Barnett, L., Seth, A.K., 2014. The mvgc multivariate granger causality toolbox: a new approach to granger-causal inference. Journal of neuroscience methods 223, 50–68.

Barrett, A.B., Barnett, L., Seth, A.K., 2010. Multivariate granger causality and generalized variance. Physical Review E 81, 041907.

Bekiros, S.D., Diks, C.G., 2008. The nonlinear dynamic relationship of exchange rates: Parametric and nonparametric causality testing. Journal of macroeconomics 30, 1641–1650.

Billio, M., Getmansky, M., Lo, A.W., Pelizzon, L., 2012. Econometric measures of connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics 104, 535–559.

BIS, 2016. Triennial Central Bank Survey of foreign exchange and OTC derivatives markets in 2016. Technical Report. Bank of International Settelement.

Blinowska, K.J., Kuś, R., Kamiński, M., 2004. Granger causality and information flow in multivariate processes. Physical Review E 70, 050902.

Chen, Y., Bressler, S.L., Ding, M., 2006. Frequency decomposition of conditional granger causality and application to multivariate neural field potential data. Journal of neuroscience methods 150, 228–237.

Cho, J.W., Choi, J.H., Kim, T., Kim, W., 2016. Flight-to-quality and correlation between currency and stock returns. Journal of Banking & Finance 62, 191–212.

Chuang, C.C., Kuan, C.M., Lin, H.Y., 2009. Causality in quantiles and dynamic stock return–volume relations. Journal of Banking & Finance 33, 1351–1360.

Clauset, A., Shalizi, C.R., Newman, M.E., 2009. Power-law distributions in empirical data. SIAM review 51, 661–703.

Csermely, P., London, A., Wu, L.Y., Uzzi, B., 2013. Structure and dynamics of core/periphery networks. Journal of Complex Networks 1, 93–123.

Diebold, F.X., Yılmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. Journal of Econometrics 182, 119–134.

Diebold, F.X., Yilmaz, K., 2015. Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring. Oxford University Press, USA.

Dungey, M., Milunovich, G., Thorp, S., Yang, M., 2015. Endogenous crisis dating and contagion using smooth transition structural garch. Journal of Banking & Finance 58, 71–79.

Eichler, M., 2007. Granger causality and path diagrams for multivariate time series. Journal of Econometrics 137, 334–353.

Estrada, E., 2007. Topological structural classes of complex networks. Physical Review E 75, 016103.

Eun, C.S., Resnick, B.G., 1988. Exchange rate uncertainty, forward contracts, and international portfolio selection. The Journal of Finance 43, 197–215.

Fawley, B.W., Neely, C.J., et al., 2013. Four stories of quantitative easing. Federal Reserve Bank of St. Louis Review 95, 51–88.

Fenn, D., 2010. Network communities and the foreign exchange market. Ph.D. thesis. University of Oxford.

Geweke, J.F., 1984. Measures of conditional linear dependence and feedback between time series. Journal of the American Statistical Association 79, 907–915.

Gillespie, C.S., 2014. Fitting heavy tailed distributions: the powerlaw package. arXiv preprint arXiv:1407.3492 .

Glasserman, P., Young, H.P., 2016. Contagion in financial networks. Journal of Economic Literature 54, 779–831.

Górski, A., Drożdż, S., Kwapień, J., 2008. Scale free effects in world currency exchange network. The European Physical Journal B-Condensed Matter and Complex Systems 66, 91–96.

Granger, C.W., 1969. Investigating causal relations by econometric models and cross-spectral methods. Econometrica: Journal of the Econometric Society , 424–438.

Granger, C.W., 1980. Testing for causality: a personal viewpoint. Journal of Economic Dynamics and control 2, 329–352.

Greenwood-Nimmo, M., Nguyen, V.H., Rafferty, B., 2016. Risk and return spillovers among the g10 currencies. Journal of Financial Markets 31, 43–62.

Han, H., Linton, O., Oka, T., Whang, Y.J., 2016. The cross-quantilogram: measuring quantile dependence and testing directional predictability between time series. Journal of Econometrics 193, 251–270.

Hojman, D.A., Szeidl, A., 2008. Core and periphery in networks. Journal of Economic Theory 139, 295–309.

Hudson, R.S., Gregoriou, A., 2015. Calculating and comparing security returns is harder than you think: A comparison between logarithmic and simple returns. International Review of Financial Analysis 38, 151–162.

IMF, 2017. Seeking Sustainable Growth: Short-Term Recovery, Long-Term Challenges. Technical Report. International Monetary Fund.

Jang, W., Lee, J., Chang, W., 2011. Currency crises and the evolution of foreign exchange market: Evidence from minimum spanning tree. Physica A: Statistical Mechanics and its Applications 390, 707–718.

Kireyev, M.A.P., Leonidov, A., 2016. A Network Model of Multilaterally Equilibrium Exchange Rates. International Monetary Fund.

Kohler, M., 2010. Exchange rates during financial crises1. BIS Quarterly Review , 39.

Kwapień, J., Gworek, S., Drożdż, S., Górski, A., 2009. Analysis of a network structure of the foreign currency exchange market. Journal of Economic Interaction and Coordination 4, 55–72.

Lee, T.H., Yang, W., 2014. Granger-causality in quantiles between financial markets: Using copula approach. International Review of Financial Analysis 33, 70–78.

Lim, J.J., Mohapatra, S., 2016. Quantitative easing and the post-crisis surge in financial flows to developing countries. Journal of International Money and Finance 68, 331–357.

Lütkepohl, H., 1982. Non-causality due to omitted variables. Journal of Econometrics 19, 367–378.

Lütkepohl, H., 2005. New introduction to multiple time series analysis. Springer Science & Business Media.

Mantegna, R.N., 1999. Hierarchical structure in financial markets. The European Physical Journal B-Condensed Matter and Complex Systems 11, 193–197.

Marinazzo, D., Pellicoro, M., Stramaglia, S., 2008a. Kernel-granger causality and the analysis of dynamical networks. Physical review E 77, 056215.

Marinazzo, D., Pellicoro, M., Stramaglia, S., 2008b. Kernel method for nonlinear granger causality. Physical Review Letters 100, 144103.

Matesanz, D., Ortega, G.J., 2014. Network analysis of exchange data: interdependence drives crisis contagion. Quality & Quantity 48, 1835–1851.

McDonald, M., Suleman, O., Williams, S., Howison, S., Johnson, N.F., 2005. Detecting a currencys dominance or dependence using foreign exchange network trees. Physical Review E 72, 046106.

Melvin, M., Taylor, M.P., 2009. The crisis in the foreign exchange market. Journal of International Money and Finance 28, 1317–1330.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012. Carry trades and global foreign exchange volatility. The Journal of Finance 67, 681–718.

Mizuno, T., Takayasu, H., Takayasu, M., 2006. Correlation networks among currencies. Physica A: Statistical Mechanics and its Applications 364, 336–342.

Newman, M., 2010. Networks: an introduction. Oxford university press.

Newman, M.E., 2005. Power laws, pareto distributions and zipf's law. Contemporary physics 46, 323–351.

Onnela, J.P., et al., 2006. Complex networks in the study of financial and social systems. Helsinki University of Technology.

Ortega, G.J., Matesanz, D., 2006. Cross-country hierarchical structure and currency crises. International Journal of Modern Physics C 17, 333–341.

Rochat, Y., 2009. Closeness centrality extended to unconnected graphs: The harmonic centrality index, in: ASNA.

Scott, H.S., 2016. Connectedness and contagion: Protecting the financial system from panics. Mit Press.

Shahzad, S.J.H., Hernandez, J.A., Bekiros, S., Rehman, M.U., 2017. Risk transmitters and receivers in global currency markets. Finance Research Letters, http://dx.doi.org/10.1016/j.frl.2017.09.018 .

da Silva Filho, O.C., Ziegelmann, F.A., Dueker, M.J., 2012. Modeling dependence dynamics through copulas with regime switching. Insurance: Mathematics and Economics 50, 346–356.

Stern, D.I., 1993. Energy and economic growth in the usa: a multivariate approach. Energy economics 15, 137–150.

Vỳrost, T., Lyócsa, Š., Baumöhl, E., 2015. Granger causality stock market networks: Temporal proximity and preferential attachment. Physica A: Statistical Mechanics and its Applications 427, 262–276.

Wang, G.J., Xie, C., 2016. Tail dependence structure of the foreign exchange market: A network view. Expert Systems with Applications 46, 164–179.

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.

Watts, D.J., Strogatz, S.H., 1998. Collective dynamics of small-worldnetworks. nature 393, 440–442.