Tail Risk Transmission in the Foreign Exchange Market: A Quantile LASSO Regression Approach

TAN T. M. LE, FRANK MARTIN & DUC KHUONG NGUYEN

Abstract We use quantile LASSO regression to investigate tail risk spillovers among the most globally traded currencies, conditional on a set of economic and financial variables. Over the study period, the tail risk of each currency was mainly driven by extreme risk spillovers from others, which became strongest in the bearish market. From the network perspective, currencies with geographical proximity tend to flock together and stronger currencies tend to be the main spreaders of extreme risk. The resulting tail-risk networks also confirm previous findings that network connectedness is asymmetric in between the extremely bullish and bearish market conditions.

Keywords: • tail risk • exchange rates • spillovers • quantile LASSO

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1 Introduction

Fluctuations of currency values play a crucial role in managing and determining the performance of cross-border activities, especially international trade and investment. In an increasingly inter-connected world, changes in value of one currency normally result in or from changes of others or both. This inter-dependence, from time to time, sparks contagion risk which can cause both micro and macro disorders. Therefore, understanding the mechanism of risk transmission among exchange rates is very important to gain the insights of many issues of international economics and finance.

Studies on risk spillovers between foreign exchange markets date back to Engle et al. (1990) who investigated the question whether intra-day volatility of exchange rate in one market is affected by volatility from other markets (meteor showers hypothesis) or only affected by country specific news (heat waves hypothesis). They found evidence to support the meteor hypothesis that volatility spillovers are popular. In a subsequent research, the study carried out by McMillan & Speight (2010) confirms the existence volatility spillover and shows the dominance of USD over CHF and JPY vis-a-vis EUR.

Starting from McMillan & Speight, studies on risk spillovers among currencies often utilize network model analyzing market connectedness. Bubák et al. (2011) used the dynamic version of the Diebold–Yilmaz (DY) spillover index (Diebold & Yilmaz, 2009) among EUR/USD and Central European currencies and reported significant increase in the degree of volatility spillovers during periods of market uncertainty, especially the subprime mortgage crisis. Diebold & Yilmaz (2015) analyzing the exchange rates of nine major currencies against the U.S. dollar from January 1999 to June 2013, also provided evidence that magnitude of volatility spillover index increased in both Global Financial Crisis (GFC) and Sovereign Debt crisis (SDC). Greenwood-Nimmo et al. (2016) generalized the framework of Diebold & Yilmaz (2012) to include spillover between blocs and applied on nine most liquid currencies vis-a-vis the USD. They found similar result as Bubák et al. (2011) and Diebold & Yilmaz (2015) with respect to the behavior of spillover index during chaotic times.

We can see from the literature that risk transmission among currencies is a popular phenomenon and that spillover is time-varying, often increase substantially in distressed markets. Nevertheless, most authors focus on the spillover of returns and variance under GARCH-type and Vector Auto Regression models while spillover of extreme risk is largely ignored. The question of whether a currency exhibits extreme loss given others are in distress is still not adequately answered. To our knowledge, there are only two researches that address this issue. Hong et al. (2009) are perhaps the first to measure tail risk spillovers in the currency market under their own theoretical framework for Granger causality in tail distribution at a particular level. In an application on intra-day exchange rates from July to September 2000, they found that large depreciation of Euro/Dollar could significantly predict large price falls of Yen/Dollar. Shahzad et al. (2018) employed the cross-quantilogram technique to identify main risk receivers and transmitters among 25 currencies from January 2000 to April 2016, focusing on the relationship between currencies of developed economies with those of emerging and Middle East and Africa. Their findings indicate that both strength and density of connections among currencies are time-dependent and vary along with different market scenarios including bearish, normal and bullish. Furthermore, currencies from developed economies are main tail risk spreaders fortified by the underlying economic links with emerging economies.

One shared limitation of these two studies is that the directional spillover between two currencies is calculated without considering the effects from the rest as well as other fundamental factors. Clearly the interactions between two variables do not occur in vacuum. The presence of these variables may alter the directions, enhance or drive down the magnitude of effects. Furthermore, like most of others, these authors focus on the lead-lag but not contemporaneous spillovers. The study in this chapter fills this literature gap by employing Least Absolute Shrinkage and Selection Operator (LASSO) quantile regression in our analysis. Thanks to its ability to shrink less relevant variables, the Lasso regression helps us to overcome the multicollinearity problem when dealing with high dimensional data (Li & Zhu, 2008). Specifically, we are able to estimate the spillovers between two currencies conditional on other currencies and a group of financial and macroeconomic variables such as interest rate difference, difference in inflation rate, state of current account and money supply growth.

Apart from that, the quantile regression technique helps us to investigate the risk spillovers in both lower and upper tail of return distributions. By this, we can explore the directional connectedness in good times or bad times of the foreign exchange markets and address questions such as: Is the spillover magnitude higher in bad times than in good and normal times? After taking account of network effects, which currency is the main tail risk transmitters (receivers) in bullish (bearish) market? Are the main transmitters of the two market conditions the same? Information on these are very useful for investors in diversifying and hedging their portfolios and regulators in monitoring currency markets (Shahzad et al., 2018)

In addition, we can rely on this framework to build a directed and weighted tail network of currencies, which is arguably more comprehensive as compared to Wang & Xie (2016) and Shahzad et al. (2018). Wang & Xie (2016) adopt the symmetrized Joe-Clayton copula to establish and examine non-directional upper- and lower-tail networks of 52 currencies. Shahzad et al. (2018) provides a directed network but on a sample of currencies which are less representative than ours. It is noteworthy that Lasso technique has been employed in establishing networks in finance like financial institutions network (Härdle et al., 2016; Hautsch et al., 2015), global banking network (Demirer et al., 2018) or credit default swaps network (Bostanci & Yilmaz, 2020). However, so far, we can find no such application in currency market. Through network analysis, we can then identify the most influential currency in risk transmission after taking into account network effects. By this we can extend Shahzad et al. (2018) who used only direct connectedness to rank currencies in terms of risk transmission.

The rest of the study is organized as follows. Section 2 presents our empirical framework. Section 3 describes relevant data while Section 4 reports the empirical results and discussion. We conclude our study in Section 5 with a short discussion and suggestions for future research.

2 Empirical framework

2.1 Lasso quantile regression model

Since invented by Tibshirani (1996) LASSO regression has been widely used and expanded recently. Suppose we want to estimate a linear relationship between Y and X where $Y = (Y_1, Y_2, \ldots Y_n)^T$ is a vector of response and X is an $(n \times p)$ matrix of predictors. The objective function in the spirit of Tibshirani (1996) is then:

$$\min_{\beta,\beta_0}\left\{\sum_{i=1}^{n}(Y_i-\beta_0-X_i^T\beta)^2+\lambda\sum_{j=1}^{p}|\beta|\right\} \qquad (1)$$

with the turning or penalization parameter $\lambda \geq 0$ According to Tibshirani (1996) and Li and Zhu (2008) L1-penalization solves this type of ordinary least square problem by shrinking some of the coefficients to exactly zero. This helps to deal effectively with the multicollinearity problem in case of high-dimensional data and increases the interpretability of the fitted model. Combining LASSO with quantile regression introduced by (Koenker & Bassett, 1978), a more comprehensive approach than classical regression with respect to statistical analysis of response models, Li and Zhu (2008) proposed the L1-norm quantile regression by considering the following regularized model fitting:

$$\min_{\beta,\beta_0}\left\{\sum_{i=1}^{n}\rho_\tau(Y_i-\beta_0-X_i^T\beta)^2+\lambda\sum_{j=1}^{p}|\beta|\right\} \qquad (2)$$

where $\tau \in (0,1)$ and ρ_τ is the check function (Koenker & Bassett, 1978)

$$\rho_\tau(Y - f(X)) = \begin{cases}\tau\cdot(Y-f(X)) & if\ \ Y - f(X) > 0\\ -(1-\tau)\cdot(Y-f(X) & otherwise,\end{cases}$$

The choice of regularization parameter λ in equation (1) plays a very crucial role. Li & Zhu (2008) mention two options to select λ: Schwarz information criterion (SIC) (Schwarz, 1978) and the Generalized Approximate Cross-Validation criterion (GACV) (Yuan, 2006).

$$SIC(\lambda) = \ln\left(\frac{1}{n}\sum_{i=1}^{n} \rho_\tau\left(Y_i - f(X_i)\right)\right) + \frac{\ln(n)}{2n} df, \qquad (4)$$

$$GACV(\lambda) = \frac{\sum_{i=1}^{n} \rho_\tau\left(Y_i - f(X_i)\right)}{n - df} \qquad (5)$$

in which df is a measure of the effective dimensionality of the fitted model.
Yuan (2006) provides solid evidence that GACV performs similarly to SIC in real data analysis while it outperforms SIC in simulation studies. We therefore choose GACV for our empirical analysis.

2.2 Currency tail risk determinants

Our study focuses on the tail connections so we will use τ = 0.05 and τ = 0.95 respectively for the extremely bearish and extremely bullish market. For the purpose of comparison, we also utilize the quantile τ = 0.5. One of the problems is to select the determinants of tail risk (as well as median returns). Let's denote W_t the set of possible determinants at time t. First of all, as in our case, we want to estimate the risk spillovers between two exchange rates conditional on the joint effects of other exchange rates so the first set of determinants of a particular exchange rate is the tail returns of the rest $E_{-i,t}$. As in Hautsch et al. (2015), in case τ = 0.05, we call $E_{-i,t}$ the extreme loss exceedances of exchange rate other than exchange rate i and defined as $E_{-i,t} = X_{-i,t}\, 1(X_{-i,t} \leq \hat{Q}_{-i,0.1})$, where $\hat{Q}_{-i,0.1}$ is the unconditional 10% sample quantile. Similarly, in case τ = 0.95, we call $E_{-i,t}$ the gain exceedances and defined as $E_{-i,t} = X_{-i,t}\, 1(X_{-i,t} \geq \hat{Q}_{-i,0.9})$, where $\hat{Q}_{-i,0.9}$ is the unconditional 10% sample quantile. For the normal market case, $\tau = 0.5$, for simplicity, we define normal market exceedances of *i* as $E_{-i,t} = X_{-i,t}\, 1(\hat{Q}_{-i,0.1} < X_{-i,t} < \hat{Q}_{-i,0.9})$.

The second set of variables should include the risk factors that reflect risk, uncertainty of the US economy. Following Adrian & Brunnermeier (2016) and Hautsch et al. (2015) we select Ted spread, the Chicago Board Option Exchange volatility index (VIX) and the Default spread index. Because the USA is the leading economy in the world, these indexes should also reflect universal risk. Hence, we name these the U_t factor, whereby *U* stands for the *US* or *'Universal'*. This set also encompasses oil returns because many among the currencies in our study belong to oil-exporting countries and because oil price fluctuations have significant impacts on the world economy (Hamilton, 1983). Last but not least are those variables in the set S_t which, theoretically, affect the value of specific currencies with respect to the US dollar. These specific factors should include but not limit to total reserve condition, current account state, money supply growth, the sensitivity to carry trade, interest rates and inflation. It is noted here that we also include the US's current account and total reserve in set *U* to balance with information in the set *S*.

As a result, we can rewrite Equation (2) for each exchange rate returns X_i within the time series context as follows:

$$\min_{\beta_i,\beta_{o,i}} \left\{ \sum_{t=1}^{n} \rho_\tau \left(X_{i,t} - \beta_0 - W_{i,t}^{\mathrm{T}} \beta_i \right) + \lambda_i \sum_{i=1}^{m} |\beta_i| \right\}, \qquad (6)$$

where $W_{i,t} \stackrel{\text{def}}{=} \{E_{-i,t}, U_{t-1}, S_{t-q}\}$, m = u + s + e - 1, u equals the number of universal variables, s is the size of the set S, e is the number of exchange rates under study, and q represents the lag number. In this study, q = 1 for all variables in *S* except for *Beta with respect to AUDJPY*, which measures the sensitivity of a certain currency to carry trade returns, where q = 26 (De Bock & de Carvalho Filho, 2015). Our empirical framework is thus innovated from both Härdle et al. (2016) and Hautsch et al. (2015) in the choice of independent variables and the type of financial markets to focus on.

2.3 Risk spillovers and tail-risk network

Equation (6) allows us to obtain relevant β. Define the estimated parameter β as: $\hat{\beta}_i \stackrel{\text{def}}{=} \{\hat{\beta}_{i|-i}, \hat{\beta}_{i|U}, \hat{\beta}_{i|S}\}$ In this set of estimated betas, $\hat{\beta}_{i|-i}$ indicates the marginal effect of extreme loss (gain) exceedances of other exchange rates on the estimated lower-(upper-) tail returns. The magnitude of estimated betas represents the strength of spillovers in each market condition. To enable comparison and calculation of spillovers, all variables in Equation (6) are normalized to take values in the range [0,1] with the following equation:

$$x_{i,t}^{norm} = \frac{x_{i,t} - min(x_i)}{max(x_i) - min\,(x_i)}$$

From the estimated beta matrix as in Table 1, we can set up the tail network following Hautsch et al. (2015). Accordingly, if the absolute value of β is bigger than or equal to 0.001, we have a directional link from exchange rate E_i to exchange rate E_j and $|\beta_{ij}|$ becomes the weight of this link. We then use network visualization and network effects to pinpoint main spillovers.

Table 1: Spillover Matrix

	E_1	E_2	...	E_i	...	E_j	...	E_n
E_1	0	β_{12}		β_{1i}		β_{1j}		β_{1n}
E_2	β_{21}	0		β_{2i}		β_{2j}		β_{2n}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
E_i	β_{i1}	β_{i2}		0		β_{ij}		β_{in}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
E_j	β_{j1}	β_{j2}		β_{ji}		0		β_{jn}
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
E_n	β_{n1}	β_{n2}		β_{ni}		β_{nj}		0

Table 2: Basic descriptive statistics of exchange rate returns

	N	Min	Max	Mean	Median	Stdev	Skewness	Kurtosis
AUD	650	-18.53	7.03	0.01	0.12	1.89	-1.70	15.74
CAD	650	-8.01	5.25	-0.01	0.06	1.34	-0.70	4.36
CHF	650	-11.44	16.67	0.04	-0.01	1.61	1.36	20.57
CLP	650	-11.62	5.86	-0.01	0.08	1.62	-1.15	7.06
CNY	650	-2.89	2.04	0.04	0.02	0.32	-0.95	15.11
COP	650	-12.74	8.80	-0.04	0.02	1.84	-0.57	5.08
CZK	650	-7.57	7.05	0.03	0.13	1.73	-0.26	1.27
DKK	650	-6.01	5.03	0.00	0.05	1.36	-0.29	1.49
EUR	650	-6.05	4.99	0.00	0.01	1.37	-0.30	1.47
GBP	650	-8.35	5.20	-0.04	-0.02	1.36	-0.66	3.59
HKD	650	-0.40	0.41	0.00	0.00	0.07	0.33	6.43
HUF	650	-8.76	8.16	-0.04	0.00	2.14	-0.35	1.84
IDR	650	-7.82	8.43	-0.05	-0.05	1.19	-0.20	10.27
ILS	650	-4.87	4.98	0.04	0.09	1.26	-0.18	1.55
INR	650	-4.50	4.77	-0.06	0.00	1.02	-0.23	2.35
JPY	650	-4.59	7.58	0.00	-0.05	1.47	0.34	1.37
KRW	650	-9.36	7.32	0.00	0.05	1.43	-0.63	6.96
MXN	650	-15.12	5.65	-0.10	-0.01	1.62	-1.41	12.73
MYR	650	-4.26	5.93	-0.01	0.04	1.04	-0.02	3.76
NOK	650	-6.42	6.73	-0.03	0.00	1.66	-0.32	0.98
NZD	650	-10.69	6.20	0.01	0.16	1.93	-0.70	2.87
PEN	650	-3.05	3.17	0.00	0.02	0.70	0.01	4.58
PHP	650	-3.28	2.94	0.02	0.04	0.80	-0.04	1.31
PLN	650	-13.04	8.45	0.00	0.13	2.04	-0.74	3.95
RON	650	-11.20	4.57	-0.04	0.07	1.66	-0.86	4.04
RUB	650	-9.96	9.75	-0.11	0.03	1.89	-0.69	5.49
SAR	650	-1.01	0.48	0.00	0.00	0.06	-4.79	110.19
SEK	650	-6.73	6.50	-0.01	0.05	1.68	-0.09	1.09
SGD	650	-4.49	2.60	0.04	0.03	0.76	-0.32	2.42
THB	650	-6.81	5.44	0.04	0.03	0.92	-0.65	10.35
TRY	650	-12.07	9.08	-0.16	-0.04	1.90	-0.51	4.25
TWD	650	-2.76	2.63	0.01	-0.01	0.64	0.11	2.21
ZAR	650	-11.28	13.62	-0.10	0.04	2.36	-0.29	3.28

Table 3: Determinants of lower-tail returns of selected exchange rate ($\boldsymbol{\tau = 0.05}$)

Currency	Determinants	
AUD	HUF, MYR, NOK, NZD, ZAR	
BRL	CLP, INR, KRW, NOK, RUB, TRY, ZAR,	Inflation
CAD	BRL, CZK, GBP, KRW, NOK, NZD, ZAR	
CHF	DKK, EUR, HUF, INR, JPY, NOK	
CNY	GBP, MYR, PHP, SEK, SGD, TWD,	Current Account US, Money Supply, Interest Rate
COP	HUF, MYR, NOK, NZD, PEN, PHP, RUB, TRY,	
EUR	CZK, DKK, HUF, NOK	
GBP	CAD, CZK, HUF, KRW, NOK, NZD, PLN, TWD	Total reserve
HUF	CZK, DKK, NOK, PLN, SEK	
INR	IDR, KRW, NOK, NZD, PHP, SGD,	Interest rate
JPY	CNY, CZK, IDR, INR, MYR, NOK, SEK	TED spread, Default spread, Current Account US
KRW	BRL, CAD, GBP, INR, MYR, NZD, PHP, SEK, TWD	
MXN	BRL, CAD, INR, MYR, RUB, SEK, ZAR	
MYR	NOK, PHP, RUB, SGD, TWD, ZAR	
NOK	CZK, HUF, MYR, SEK	
PLN	CZK, HUF, SEK,	
RON	CZK, DKK, HUF, NOK, SEK	
RUB	MYR, NOK	Current Account, Inflation, Interest Rate
SEK	CZK, EUR, HUF, INR, NOK	
SGD	DKK, EUR, MYR, NOK, SEK, TWD	
THB	IDR, INR, NOK, PHP, TRY, TWD, ZAR	Current Account US, Money Growth
TRY	BRL, HUF, KRW, NZD, ZAR	Total Reserve
ZAR	HUF, MYR, NOK, TRY, TWD	

3 Empirical data

This study uses weekly exchange rates of top 34 globally traded currencies against the USD. According to BIS (2016), annual trading between these currencies against the USD accounts for around 80% of all pairs. In order to limit missing values, we choose the sample period from 17 July 2005 to 31 December 2017, making a total of 650 observations. This sample period witnessed several important events which preceded changes in foreign exchange markets. For example, the date 21 July 2005 witnessed the change in exchange rate policy of both China and Malaysia from fixed to managed floating regime. Other major events include the Global Financial Crisis, Sovereign Debt Crisis, the Brexit referendum as well as the rising of protectionism powered by president Donald Trump in 2017. Augmented Dickey - Fuller tests reveal that exchange rates have unit root in level; thus, weekly log returns are utilized for the analysis. To facilitate interpretation, we assign the USD to be the counter currency in every exchange rate. Thus, an increase in log return is translated into an appreciation of relevant currency vis-a-vis the USD while a decrease demonstrates the otherwise.

Data on VIX index, Ted spread, default spread, stock market indexes, interest rates and oil prices are obtained with weekly frequency. For the regression, differences in stock log returns and differences in three-month interest rates between countries in our sample and the United States are employed. To ensure the comparability, we use MSCI stock indexes for all countries except Romania because of data inadequacy. Since Augmented Dickey - Fuller (ADF) tests cannot reject the null that the above-mentioned risk series have unit roots, we use the first difference for TED and default spread and log difference for VIX index in our analysis. Data with quarterly or monthly frequency including current account to GDP, GDP index, total reserve, CPI index, money stock are converted to weekly frequency using cubic interpolation following Hautsch et al. (2015) and Härdle et al. (2016). We use broad money M3 as a proxy for money supply in all cases except for Romania, Taiwan and Romania where M2 is used instead. Our last variable is Beta with regard to AUDJPY for each currency, which measures the sensitivity of relevant currencies to carry trade returns in the. AUDJPY beta of each exchange rate is obtained by regressing changes in that exchange rate on the changes of AUDJPY over a sample 52 weeks to week *t*, as suggested by De Bock & de Carvalho Filho (2015). *All data is sourced from Bloomberg terminal*. Basic descriptive statistics of exchange rate returns from 2005 to 2017 can be seen from Table 2; that of other variables will be provided upon request.

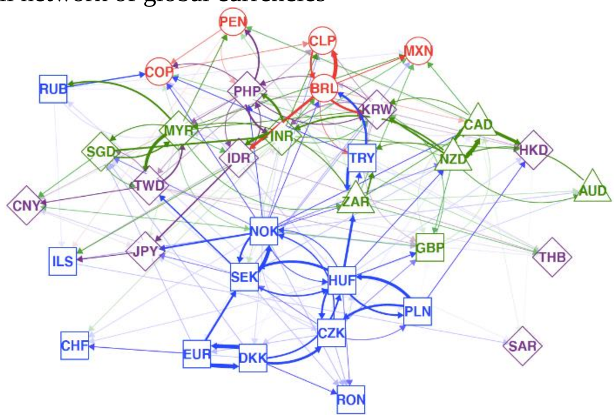
4 Results and discussion

Table 3 provides the list of determinants of lower-tail returns for thirty-four currencies under study. It can be seen that tail returns are driven by variables in all three sets mentioned in Section 2, among which extreme loss exceedances from other currencies are the main drivers. In fact, in bearish markets, universal and specific variables only affect fourteen out of thirty-four currencies while loss exceedances appear in every case.

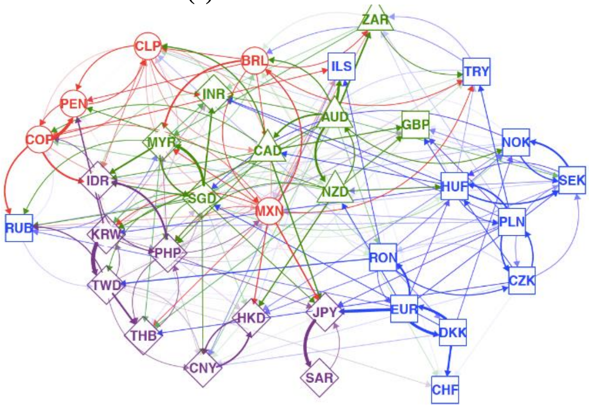
This finding partly agrees with Hautsch et al. (2015) who find that loss exceedances are the only determinants of tail risk of fifty seven major US financial institutions from 2000 to 2008. Similar results are obtained from extremely good market condition. Furthermore, in normal markets variables other than exceedances seem to almost have no role in determining the value of exchange rates (evidence will be provided upon request). We can thus come to conclusion that market states strongly impact the relationship between currencies as well as between currencies and fundamentals. Extreme loss/gain exceedances are dominant tail risk drivers while the effect of other variables is somewhat limited.

From the results of quantile lasso regression, two tail networks can be visualized as in Figure 1, whereby the upper and lower part presents extremely bearish and bullish directional connections relatively.

Figure 1: Tail network of global currencies



(a) Lower tail network



(b) Upper tail network

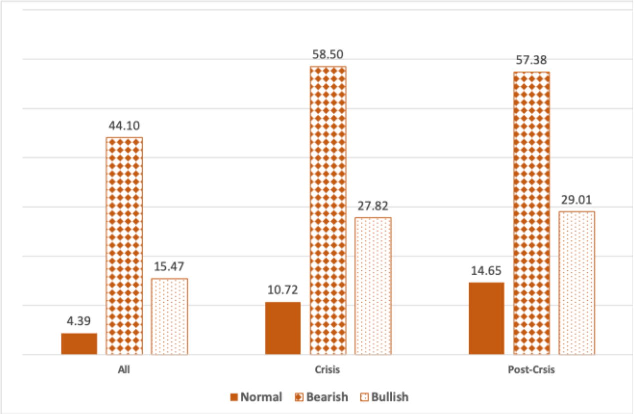
We use colors and shape to indicate different currency groups. The red circle indicates Latin America, the blue or square is for Europe, the purple or diamond for Asia, the triangle or green represents commonwealth countries. Each arrow indicates the direction of spillovers while its width reflects spillover strength. Mathematically, for example, the higher the absolute value of $\hat{\beta}_{EUR|JPY}$ in Table 1, the higher the tail risk spillover from USDEUR to JPYEUR, which turns into the thicker arrow from EUR to JPY. It is obvious from Figure 1 that currencies from countries/territories with geographical proximity (e.g. in the same continent) are generally more connected to each other and tend to have mutual relationships. Currencies of Norway and Sweden (NOK & SEK), Chile and Brazil (CLP & BRL), Hungary and Poland (HUF & PLN), Indonesia and the Philippines (IDR & PHP), Australia and New Zealand (AUD & NZD), Taiwan and Singapore (TWD & SGD) prove such examples. This is easily understood as countries located close to each other often have strong international trades, investments and other international relationships. Some currencies that do not share physical borders but belong to countries within a particular bloc also show strong connectedness. For example, the Canadian dollar, New Zealand dollar, Australian dollar and British Pound all belong to commonwealth group. It is noted, however, that the spillover relationship between currencies, even in the same group, changes in between different market states. For instant, there exist mutual spillovers between MXN and BRL in the extremely bullish market but not in the opposite market condition. Similar phenomenon is seen between CNY and HKD, EURO and RON, KRW and TWD. This highlights the importance of quantile analysis on risk spillovers in the foreign exchange market.

The general spillover statistics are summarized on Figure 2. Here the crisis period ranges from July 2, 2007 to September 15, 2012, covering both the global financial crisis and the European Sovereign debt crisis. Post crisis period lies in between September 16, 2012 to the end of 2017. We do not include the pre-crisis period to avoid spurious results since some exchange rate returns and their relevant gain/loss exceedances are not stationary. The lower part of this figure provides information about the number of significant spillovers while the upper part presents total weight or strength of spillovers corresponding to three market scenarios: normal, extremely bearish and extremely bullish. Total weight is obtained by taking the sum of outgoing weights of the thirty-four currencies.

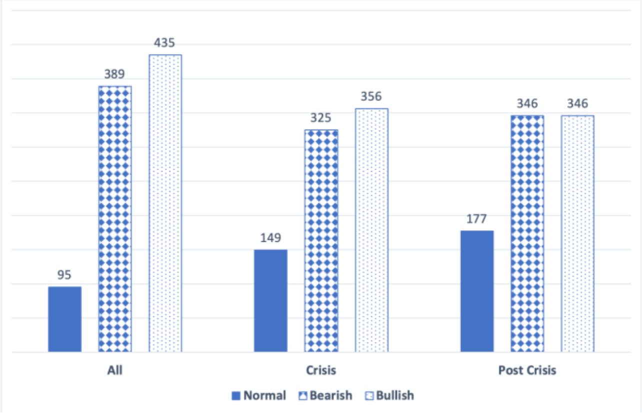
It is obvious that spillovers vary along with the time frame, general states of economy and especially different states in the foreign exchange markets. The strongest spillover is found in the crisis period corresponding to the bearish market ($\sum W_i = 58.50$). In every period, spillover strength is always at peak when the foreign exchange market is in distress. It can also be seen that both links and in weights in normal market are about two times less than that in the other two extremes. This means currencies are more connected in extremely good or extremely bad times compared to normal times and that stronger connection is found in distressed times compared to vigorous market conditions.

The normal market is characterized by the struggle between up and down swing or, put it differently, there is no clear-cut direction. The 'wait-and-see' strategy therefore becomes popular in the market. As a result, spillover among currency is lower than in the two other market states. The fact that lower-tail spillover is greater than upper-tail spillover can possibly be explained by the loss spiral and the margin/haircut spiral in Brunnermeier et al. (2008): big losses cause funding problems for investors and hence they have to reduce their positions by selling the relevant currencies for USD which in turn cause further losses on the current positions and ignite higher margin requirements and so on. Losses on one currency may spread to others through rebalancing or through indiscriminate selling or herd behavior under information asymmetry (Dornbusch et al., 2000; Scott, 2016). These findings partly agree with previous studies by Shahzad et al. (2018), Wang and Xie (2016) , Greenwood-Nimmo et al. (2016) and Leung et al. (2017).

Figure 2: Overall risk spillovers among global currencies



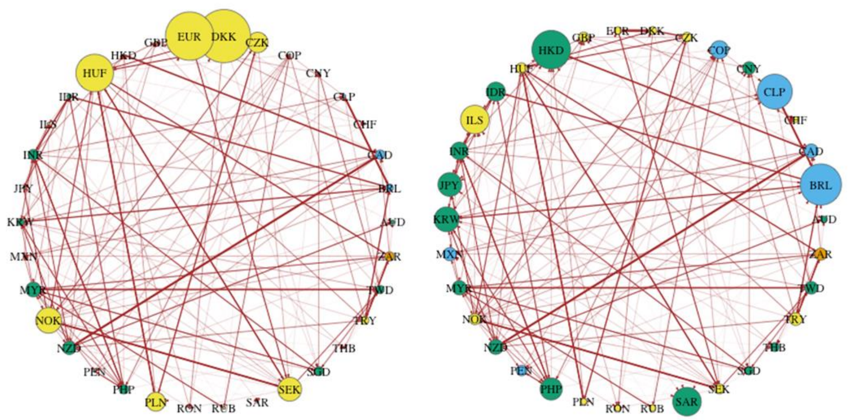
(a) Total spillovers



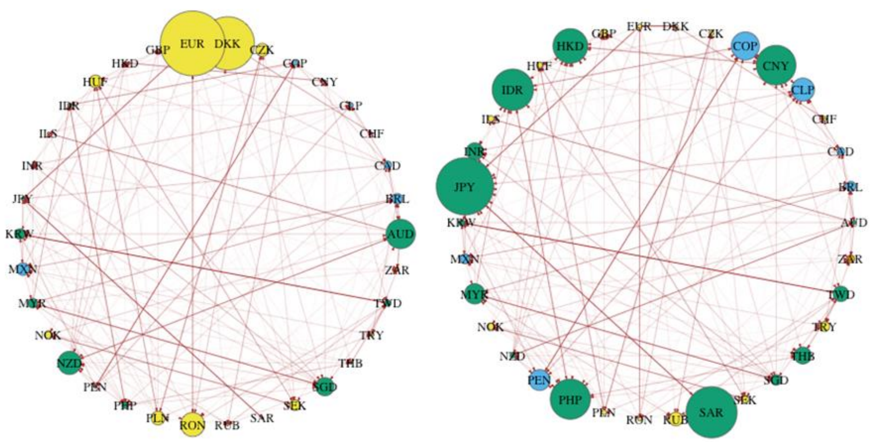
(b) Total links

Surprisingly, while the spillover strength in bearish market doubles that in bullish market, the total number of directional links relating to the latter tend to exceed that in the former. As an example, the total links in these two market conditions are relatively 435 compared to 389 for the entire period. Perhaps bearish markets often go hand in hand with contagion, thus, governments around the world are more likely to apply capital control measures in order to prevent the spread of risk to their domestic markets. This potentially explains why there are fewer links in extremely bad market condition as compared to extremely good one.

Figure 3: Main transmitters (left) and receivers (right)



(a) Extremely bearish



(b) Extremely bullish

To answer the question which are the main extreme risk transmitters and receivers and whether their positions change in accordance with the two extreme states, we employ the Page Rank centrality (Csardi & Nepusz, 2005) to take into account both direct and indirect effects. As shown in Figure 3, the EUR and the DKK are the two top risk spreaders in both market states. The EUR tops the ranking in bullish market but switches position for the DKK in the bearish market. This is not surprising since the DKK is pegged to the EUR, it become more volatile when the general economic state worsen, thus, have more impacts on others than the EUR. Figure 3 also shows that the Asian currencies are more likely to benefit in extremely good times while currencies from Latin America seem to be the most.

5 Conclusion and future research

Over the period from July 2005 to 2017, the tail risk of each currency was mainly driven by spillovers from others with risk spillovers varying across different states of foreign exchange market and of the global economy. Market states create asymmetric risk spillovers among currencies. They change the number of links, overall strength, the relationship between each pair of currencies as well as their positions as main risk receivers or spreaders. Stronger spillovers are observed in bearish market and in global distressed economic conditions. The resulting tail networks confirm a well documented phenomena in literature that currencies with geographical proximity tend to be more connected to each other.

The paper can be extended by spanning over the Covid-19 period, the Russia-Ucraine conflict period and by including rolling-window regression to see dynamic tail-risk spillovers over time.

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