Currency downside risk, liquidity, and financial stability

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Abstract

We estimate volatility- and quantile (depreciation)-based spillovers across 20 global currencies against the US Dollar. In so doing, we reveal significant asymmetries in the propagation of risk across global currency markets. The quantile-based statistic reacts more significantly to events that have a sizable impact on FX markets (e.g. Brexit vote and the FX crash following the subprime crisis), which are missed by the volatility-based statistic. As such, our tail-spillover estimates constitute a new financial stability index for the FX market. This index has the advantages of being easy to build, of not requiring intraday data and of being more informative about currency crises and pressures than traditional spillover statistics based on volatilities. Finally, we also document differences in the relation between liquidity and volatility (quantile) spillovers.

JEL Codes: E44, F31, G01, G12, G15.

Key Words: foreign exchange, spillovers, currency crises, networks.

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1. Introduction

Currency crises have been of particular concern for policy-makers, regulators, practitioners and academics since at least the post-Bretton Woods era (Krugman, 2000). In the intervening years, one of the most frequently examined – albeit one of the least understood – issues related to such crises have been the mechanisms of propagation of currency shocks, be they a consequence of macro-fundamentals, coordinated polices, common-lenders, speculative attacks or simply a result of unexpected (or unexplained) mechanisms (pure-contagion)[1]. Yet, co-movements and risk spillovers in currency markets can have an enormous economic and social impact on financial and macroeconomic stability and, hence, on wellbeing[2]. Currency shock spillovers have been shown to be closely linked to global imbalances, investor speculation, sovereign debt concerns (Chen, 2014), sudden stops, sharp real depreciations and asset price crashes (Apostolakis and Papadopoulos, 2015; Korinek and Mendoza, 2014) and, therefore, to financial collapses. Currency trading, measured in dollar volume, represents the largest financial market on the planet: an average of $5.1 trillion each day according to the latest Triennial Central Bank Survey conducted by the Bank for International Settlements (Bank of International Settlements, 2016). Hence, understanding spillovers in foreign exchange (FX) markets is critical for maintaining financial stability.

There is a well-established branch of the macro-financial literature that empirically studies spillovers in FX markets (Baillie and Bollerslev, 1990; Engle et al., 1990; Ito et al., 1992; Hogan and Melvin, 1994, Hong, 2001; Melvin and Melvin, 2003; Cai et al., 2008; Bekiros and Diks, 2008; Bubák et al., 2011; Coudert et al., 2011; Li, 2011; Antonakakis, 2012; Kavli and Kotzé, 2014; Diebold and Yilmaz, 2015; Greenwood-Nimmo et al., 2016). Some of these studies focus specifically on spillovers between highly traded currencies (for instance, Greenwood-Nimmo et al., 2016) while others also include emerging market currencies with lower trade volumes (e.g. Kavli and Kotzé, 2014; Coudert et al., 2011).

The study of return and volatility spillovers in currency markets imposes its own symmetry on the analysis, by implicitly assuming that for any given country the situation is roughly the equivalent of facing depreciation or appreciation pressures[3]. This assumption is at the very least controversial. In the worst-case scenario, central banks may *lean against the wind* when appreciation pressures emerge on the horizon, to the degree that they are willing (or politically allowed) to do so. On the other hand, their response is much more restricted when faced by an episode of depreciation. Here, in the worst case they are bound by the (frighteningly) lower limit of the FX reserves.

The aim of this paper is to analyze *downside* risk propagation across global currency markets and the ways in which it is related to liquidity. We make two primary contributions to the literature. First, we estimate *tail-spillovers* between currencies in the global FX

[1] See Rigobon (2002) and references therein for a discussion about contagion, including currency markets.

[2] See Krugman (2000) and references therein.

[3] The importance, on empirical grounds, of considering asymmetries when modeling exchange rate variations has been documented for instance by Patton (2006) and Reboredo et al. (2016). Unlike the analysis reported herein, these studies neither consider dynamic spillovers nor focus on currency crises and systemic risk, rather they model pairs of series – the Deutsche Mark and US Dollar in the former case and stock returns against exchange rates for emerging economies in the latter.

market. Unlike previous studies that focus on return co-movements and volatility spillovers in currency markets, we directly address the issue of risk spillovers in the left tail of the daily variations in currency prices (depreciations). We do so by closely adhering to what we consider a key element in the definition of a currency crisis proposed by Paul Krugman: "[it] is a sort of circular logic, in which investors flee a currency because they fear that it might be *devalued*, and in which much (though not necessarily all) of the pressure for such a *devaluation* comes precisely from that capital flight" (Krugman, 2000, p 1. The emphasis is ours). Notice that by definition currency crises are related to periods of depreciation (or devaluation), and not to episodes of appreciation (or revaluation). Thus, in terms of financial stability, episodes of depreciation are more significant than those of appreciation.

Our strategy allows us to consider specifically *downside risk* in currency markets, corresponding in this instance to episodes of *depreciation* of the global currencies against the US dollar. This is more consistent with the definition of a currency crisis. Indeed, there exists recent empirical evidence that points out the asymmetric propagation of volatility shocks depending on whether they are related to depreciation or appreciation episodes (or correspondingly to bad and good volatility shocks). Galagedera and Kitamura (2012) model the interaction between returns and volatility in an autoregressive system that accounts for asymmetries in the propagation of shocks. These authors show that during the subprime crisis the depreciation of the US dollar against the Japanese yen produced a larger impact on US dollar-yen volatility spillover than appreciation did. Not such an effect was observed for the U.S. dollar against the euro. In the same general lines, Baruník et al. (2017) document dominating asymmetries in spillovers, which are due to bad rather than good volatility. They also show that negative spillovers seen to be tied to sovereign debt concerns, while positive spillovers have been mainly associated with the global financial crisis. These asymmetries are fundamental to our study of extreme depreciation quantiles. Additionally, our tail-spillover estimates can be used to construct a new financial stability index for the FX market. This index is easy to build and does not require intraday data, which constitutes an important advantage.[4]

Our second contribution is that we explore whether turnover is related to risk spillovers in global currency markets. In this respect we draw inspiration from Mancini et al. (2013) and Karnaukh et al. (2015), who document a significant relationship between currency liquidities (i.e. commonality). Our intuition is that liquidity matters for spillovers. World currencies can be expected to behave differently depending on how much investors trade them and, in turn, commonality may become evident by examining the dynamic spillovers in worldwide FX markets.

In line with Diebold and Yilmaz (2015), we opted to include in our sample of 20 currencies against the US dollar those with high trading volume ratios (Euro, Yen, British Pound, Australian Dollar, Canadian Dollar, Swiss Franc, Swedish Krona, Mexican Peso, New Zealand Dollar, Singapore Dollar, and Norwegian Krone) as well as those with considerably lower market transaction levels (South Korean Won, Turkish Lira, Indian Rupiah, Brazilian Real, South African Rand, Polish Zloty, Thai Baht, Colombian and Philippine Pesos). In this way, we seek to provide a more comprehensive panorama of global FX market dynamics.

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[4] Our index is available on http://www.ub.edu/rfa/currency-crisis-index/

Our methodology consists of two steps. First, we estimate intraday range volatilities and conditional quantiles. Then we use these series as input to construct traditional Diebold and Yilmaz (2012, 2014) statistics, net pairwise statistics and networks. Obvious alternatives for constructing asymmetric spillovers are semi-variances (Barndorff-Nielsen et al., 2010). However, these semi-variances, especially the measure of 'bad volatility', are based on 'fill-in asymptotics', and require intraday prices to be computed on a daily basis. Our measure is based on conditional quantiles and does not require this level of detailed information. Second, our measure focuses specifically on a high depreciation-quantile (VaR at 95% of confidence), as opposed to the full spectrum of 'bad volatility', which refers approximately to 50% of the variations. It is our contention that the two steps outlined above represent compelling advantages of our proposal.

We document significant asymmetries in terms of risk propagation that become evident after comparing volatility-based and quantile-based spillover measures. The quantile-based statistic reacts more significantly to events that have a sizable impact on FX markets (e.g. the Brexit vote and the FX crash following the subprime crisis), which are missed by the volatility-based statistic. We also gain insights into the relation between liquidity and spillovers. For example, while Karnaukh et al. (2015) document that the most liquid currencies are more strongly affected by global risk factors during turbulent times, we complement this analysis by showing that during the subprime crisis and its aftermath (between 2008 and 2012) the most liquid currencies not only behaved as net-receivers of volatility shocks (in this respect in line with Karnaukh et al., 2015), but also that this pattern is reversed for the period 2012-2016, indicating that the most liquid currencies are also able to destabilize the rest of the market during episodes of relative calm. Interestingly, the shocks propagate as in *a cascade*: the more liquid a set of currencies is, the more likely *it affects* all the other currencies, *during periods of depreciation* (against the USD). Conversely, the more liquid it is, the more likely *it is affected* by all the other currencies *during turbulent periods that lack a clear trend* in terms of appreciation or depreciation.

Our analyses provide new perspectives on the relation between liquidity and volatility (quantile) spillovers. In the case of tail-spillovers, most liquid currencies are, by rule, net-receivers and the least liquid currencies are net-transmitters. However, in the case of volatility spillovers, the (receiving or transmitting) role of the currencies is sorted by liquidity changes during periods of depreciation, appreciation or turbulence.

The asymmetries in the propagation of shocks that become evident when we compare quantile and volatility spillovers may be due to the different nature of the risk faced by emerging and mature markets, regarding currency crises, sudden stops and continuous portfolio reallocation by international fund managers. While for emerging markets depreciation pressures are a dramatic concern, which may potentially destabilize their balance of payments, for mature economies with more liquid currencies, appreciation or depreciation is more related to an issue of portfolio diversification with smaller consequences for the real economy. Therefore, when it comes to the depreciation quantiles, the risk transmitted by emerging markets, issuing less liquid currencies, becomes fundamental under any scenario (they are always net-transmitters), while when it comes to volatilities a more complex dynamics arises. In periods of US dollar appreciation/depreciation international outflows/inflows led by the continuous rebalancing of international investors, and carry trade strategies, produce the cascade effect mentioned before.

That is, during US dollar appreciation periods usually depicted by a panorama of flight to quality, in which international investors are reversing their positions hold in less liquid currencies in order to invest in assets denominated in US dollars (safer and more liquid), big currencies may destabilize the system generating shocks larger than those that they receive. Time varying risk aversion may also play and important role in this narrative. Risk-averse investors likely respond more sensitively to valuation changes of their foreign asset holdings during stress times. And this could propagate downside risk across global currency markets. Aggregate risk aversion may fluctuate either because the risk aversion of the representative investor changes or because the distribution of wealth among investors with different risk aversion changes. Variation of risk aversion becomes a first order candidate to explain the dynamics described above, due to the fact that our sample period houses the major financial crisis of the last 80 years in the global markets. Indeed the previous literature has provided convincing evidence on a shift in risk aversion following the subprime crisis. On the one hand, Bekaert et al. (2013) and Bekaert et al. (2017) decompose the VIX into a time-varying risk aversion component and a pure volatility component (or what they call uncertainty), and they document an increase of risk-aversion during the global financial crises, its aftermaths, and the during the European debt crisis. On the other hand, Guiso et al. (2017) have recently provided evidence on a shift in individual risk aversion following the global financial crisis. They do so by exploiting portfolio choices and survey-based measures of risk aversion elicited in a sample of clients of a large Italian bank in 2007 and repeated on the same set of people in 2009.

The significant asymmetries that we reveal by contrasting quantile- and volatility-based measures of spillovers are critical for financial stability, and should be taken into consideration when conducting exercises that seek to monitor financial fragility around the world. Our findings are also relevant for designing the hedging mechanisms that are of such instrumental importance for international investors. For example, international mutual fund managers tend to hold portfolios within certain target regions such as BRICs, Latin American, and Asian markets, etc. As a result, exchange rate volatility spillovers among neighboring countries may damage the benefits of the international investors' portfolio diversification. This consideration is especially relevant in the face of depreciation spillovers, which become fundamental to understand diversification benefits from investing in non-mature markets. Emerging markets are particularly vulnerable to currency crises and depreciation pressures and, therefore, to depreciation spillovers as those targeted by our analysis. Certainly, volatility and quantile spillovers are also instrumental when it comes to understand the speed of market adjustment to new information, and the extent to which a given country is vulnerable to potential contagion. Historical episodes such as the Asian crisis, the Russian crisis, the Argentinian debt crisis or even the European sovereign debt crisis motivate our approach, which involves evaluating the risk of investment denominated in a foreign currency in a direct fashion.

The rest of the paper is organized as follows. Section 2 presents the methodological approach we adopt and section 3 describes our data. The results of the spillover analysis are discussed in section 4 and section 5 concludes.

2. Methodology

We used variance decomposition of forecast errors, as proposed by Diebold and Yilmaz (2012), to analyze spillovers between range-based volatilities and between quantiles of daily log-variations in foreign exchange markets. To estimate the latter, we employed an asymmetric slope Conditional Autoregressive Value at Risk model (CAViaR) as introduced by Engle and Manganelli (2004). We also used graphical networks to analyze specific dates in the foreign exchange markets, in line with Diebold and Yilmaz (2014).

2.1. *Volatility Measure*

We calculated the volatilities of each of the 20 currencies using the range-based volatility framework proposed by Parkinson (1980). We opted for this framework given its efficiency and simplicity both of estimation and interpretation (Alizadeh et al., 2002). The daily variance of each market *i* is calculated based on the highest and lowest daily prices on day *t* as follows:

$$\bar{\sigma}_{it}^2 = 0.361[\ln Emax_{it} - \ln Emin_{it}]^2, \qquad (1)$$

where $Emax$ is the highest price of currency i on day t and $Emin$ is the lowest price of currency *i* on day *t* for $i = 1, \ldots N$ and $t = 1, \ldots, T$. The annualized volatility in percentage points was calculated as:

$$\tilde{\sigma}_{it} = 100\sqrt{365\ \bar{\sigma}_{it}^2}. \qquad (2)$$

2.2. *CAViaR model*

The CAViaR model for variable y_t can be expressed as:

$$q_t(\beta,\alpha) = \delta_0(\alpha) + \sum_{i=1}^{s} \delta_i(\beta,\alpha)\, q_{t-i}(\alpha) + \sum_{j=1}^{p} \gamma_j(\alpha)\, F\big(x_{t-j},\omega\big), \qquad (3)$$

Where $q_t(\beta,\alpha)$ is the α quantile at time *t* of the variable y_t, which in our case corresponds to the daily log variation of each FX in our sample ($y_t = \ln E_t - \ln E_{t-1}$), β is a vector of unknown parameters of size *p*, and α is the level of confidence of the associated VaR. The second term in the right hand-side of the equation relates to the autoregressive component that allows for the smooth dynamics of the quantile, while the third term is related to the conditioning variables (x_t) and the information set (ω). Specifically, the asymmetric slope CAViaR can be expressed as:

$$q_t(\beta,\alpha) = \beta_0(\alpha) + \beta_1(\alpha) q_{t-i}(\beta,\alpha) + \beta_2(\alpha) {y_{t-1}}^{-} + \beta_3(\alpha) {y_{t-1}}^{+}, \qquad (4)$$

where y_t^- and y_t^+ are the negative and positive values of y_t, respectively. This specification captures the asymmetric effect in the slope of the quantile, conditional on the value and on the sign of the returns.

The CAViaR model was estimated following the quantile regression framework provided by Koenker and Bassett (1978). In this framework, the parameters are estimated as a special case of the least absolute deviation (LAD) estimator. The maximization of the likelihood function was performed using numerical methods (BFGS quasi-Newton with Hessian updates).

2.3. *Spillover measures*

The spillover indices are based on a VAR with *N=20* variables, and were built on the associated forecast error variance decomposition (FEVD). The errors were estimated from the moving average representation of the VAR as follows:

$$X_t = \Theta(L)\varepsilon_t, \tag{5}$$

$$X_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}, \tag{6}$$

where X_t is a matriz $T \times N$, $\Theta(L) = (I - \phi(L))^{-1}$, ε_t is a vector of independently and identically distributed disturbances with zero mean, and Σ covariance matrix, $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-1} + \cdots + \phi_p A_{i-p}$ is the parameters' matrix, *p* is the number of lags used in the estimation, and *T* is the number of periods. To estimate the FEVD from the h-step ahead forecast, we first had to identify the structural VAR innovations by imposing restrictions on the MA parameters. In line with Diebold and Yilmaz's suggestion (2012), we followed the eclectic path proposed by Koop et al. (1996) and Pesaran and Shin (1998), namely the generalized VAR, for the construction of the FEVD.

The errors in the FEVD can be divided into *own variance* shares and *cross variance* shares. The former are the fractions of the errors that are related to a shock to x_i on itself, while the latter are the portion of the shocks on x_i related to the rest of the variables in the system. The h-step ahead FEVD can be defined as:

$$\theta_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)}, \tag{7}$$

Where Σ is the covariance matrix of the error vector, σ_{jj} is the *j*-th diagonal element of Σ, and e_i is a selection vector with ones in the *i*-th element and zeros otherwise. To guarantee that the sum of each row is 1, $\sum_{j=1}^{N} \tilde{\theta}_{ij}(H) = 1$, each entry of the variance decomposition must be normalized as follows:

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(H)}{\sum_{j=1}^{N} \theta_{ij}(H)}. \tag{8}$$

where $\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H) = N$.

With the normalized variance decomposition, a total spillover index can be calculated as:

$$C(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100. \quad (9)$$

This index measures the percentage variance that can be explained by cross-spillovers. It can be extended to a *directional spillover* index, in which the effect of a shock from all other markets j on the variable x_i is given by:

$$C_{i \leftarrow j}(H) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100, \quad (10)$$

conversely, the effect of a shock from x_i on all other markets j is given by:

$$C_{i \rightarrow j}(H) = \frac{\sum_{j=1, i\neq j}^{N} \tilde{\theta}_{ji}(H)}{N} \times 100, \quad (11)$$

with the two directional spillover indices we construct the *net spillover* index as:

$$C_i(H) = C_{i \rightarrow j}(H) - C_{i \leftarrow j}(H). \quad (12)$$

The net spillover index is a measure of the effect related to a shock in the variable x_i on the rest of the system. Therefore, each market will be either a *net receiver* or a *net transmitter* of shocks in each period. It is also possible to construct a *net pairwise spillover* index, that accounts for the net spillover effect of the exchange rate x_i on x_j, where $i \neq j$. The net pairwise index can be defined as:

$$C_{ij}(H) = \frac{\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H)}{N} \times 100. \quad (13)$$

2.4. *Networks*

In line with Diebold and Yilmaz (2014, 2015), we also employed graphical network analysis. Unlike those authors, we used graphs to highlight the differences between volatility-based and quantile-based measures in FX markets. Nodes and edges constitute network graphs: the former given by a certain currency and weighted according to the turnover of this currency during the last year in the sample; and the latter by the net pairwise spillover indices on a certain date. In Figure 6 we only include the highest quartile of the net pairwise statistics so as to better appreciate the main results.

3. Data

We use a database comprising twenty of the most traded currencies per US dollar (US dollar/domestic currency) that have either a free floating, floating or managed floating exchange rate regime (see Table 1). Currency selection was based on the information provided by the Bank of International Settlements' Triennial Central Bank Survey of foreign exchange and OTC derivatives markets (Bank of International Settlements, 2016). This report ranks foreign exchange currencies according to their daily turnover. The exchange rate regime for each of the currencies was obtained from the International Monetary Fund's Annual Report on Exchange Arrangements and Exchange Restrictions (International Monetary Fund, 2014).

We retrieved the data that correspond to the close, high and low quotes of the exchange rates from Bloomberg. Our data span the period January 1, 2003 to September 5, 2016, for a total of 3,569 daily observations for each of the currencies. The year 2003 was chosen as the starting date in order to include in our database emerging market currencies (including the Colombian Peso and the Polish Zloty) that did not adopt a floating or managed floating exchange rate regime until around this date. We omit countries with fixed exchange rate regimes because their artificially low exchange rate risk would bias the results.

Table 1. Selected currencies ordered according to turnover

Code	Currency	Country	Exchange Regime
EUR	Euro	Europe	Free Floating
JPY	Yen	Japan	Free Floating
GBP	Pound Sterling	United Kingdom	Free Floating
AUD	Australian Dollar	Australia	Free Floating
CAD	Canadian Dollar	Canada	Free Floating
CHF	Franc	Switzerland	Managed Floating
SEK	Swedish Krona	Sweden	Free Floating
MXN	Mexican Peso	Mexico	Free Floating
NZD	New Zealand Dollar	New Zealand	Floating
SGD	Singapore Dollar	Singapore	Managed Floating
NOK	Norwegian Krone	Norway	Free Floating
KRW	Won	South Korea	Floating
TRY	Lira	Turkey	Floating
INR	Rupee	India	Floating
BRL	Real	Brazil	Floating
ZAR	Rand	South Africa	Floating
PLN	Zloty	Poland	Free Floating
THB	Baht	Thailand	Floating
COP	Colombian Peso	Colombia	Floating
PHP	Philippine Peso	Philippines	Floating

Source: Bank of International Settlements (2016) and International Monetary Fund (2014).

3.1. *Descriptive statistics of daily log variations in FX markets*

Table 2 provides the summary statistics of the annualized FX log returns in our sample. In Tables A1 and A2 in the appendix we provide descriptive statistics for the estimated volatilities and VaRs. FX returns are characterized by heavy tails and some by negative skewness. The ZAR displays the highest one-day depreciation in the sample, with a 15 percent drop in October 2008. The range (difference between daily max. and min.) of the currencies of the developing economies and the commodity exporting countries is, in general, greater than that of the currencies of the developed economies. Consistent with this, the former currencies present higher risk, with a greater standard deviation, than that presented by the mature markets.

Table 2. Summary statistics of annualized FX log returns. Our data span January 1, 2003-September 5, 2016. We use a database comprising twenty of the most traded currencies per US dollar (currency/US dollar) that have either a free floating, floating or managed floating exchange rate regime.

	EUR	**JPY**	**GBP**	**AUD**	**CAD**	**CHF***	**SEK**	**MXN**	**NZD**	**SGD**
Mean	0.03	0.04	0.00	0.08	0.05	0.08	0.04	-0.03	0.08	0.03
Median	0.03	0.00	0.00	0.14	0.04	0.00	0.03	0.04	0.14	0.06
Maximum	13.42	14.92	11.27	35.25	15.64	103.58	20.20	27.45	17.09	7.28
Minimum	-8.50	-18.12	-26.40	-23.38	-11.19	-28.25	-14.30	-22.57	-21.81	-7.89
Std. Dev.	2.29	2.36	2.16	3.10	2.24	3.05	2.89	2.61	3.12	1.13
Skewness	0.19	0.27	-0.66	0.18	0.03	10.96	0.18	-0.16	-0.14	-0.30
Kurtosis	4.80	7.25	11.12	13.80	5.51	378.48*	5.92	12.96	5.37	7.48
	NOK	**KRW**	**TRY**	**INR**	**BRL**	**ZAR**	**PLN**	**THB**	**COP**	**PHP**
Mean	0.02	0.04	-0.01	-0.02	0.08	0.03	0.06	0.03	0.04	0.02
Median	0.00	0.04	0.12	0.00	0.00	0.07	0.11	0.00	0.00	0.00
Maximum	19.67	37.33	25.89	13.51	32.25	28.56	26.28	14.09	31.92	8.10
Minimum	-16.26	-25.32	-23.92	-10.95	-21.23	-43.22	-16.87	-22.64	-22.10	-9.28
Std. Dev.	2.92	2.71	3.17	1.69	3.75	4.10	3.41	1.56	2.86	1.40
Skewness	0.03	1.11	-0.26	0.05	0.16	-0.32	0.08	-0.87	0.53	-0.02
Kurtosis	5.52	31.03	9.23	9.24	8.40	9.18	6.97	32.21	14.04	5.24

*In September 2011, the Swiss National Bank adopted a fixed exchange rate with the Euro and, subsequently, in January 2015, it abandoned the peg. These two episodes explain the abnormal maximum, kurtosis and skewness of the Swiss Franc (CHF). Except for these episodes, the CHF is remarkably stable, with a standard deviation of 2.46, a skewness of 0.37, and a kurtosis of 6.54. We include it in our sample due to its historical and financial importance as a 'haven' currency.

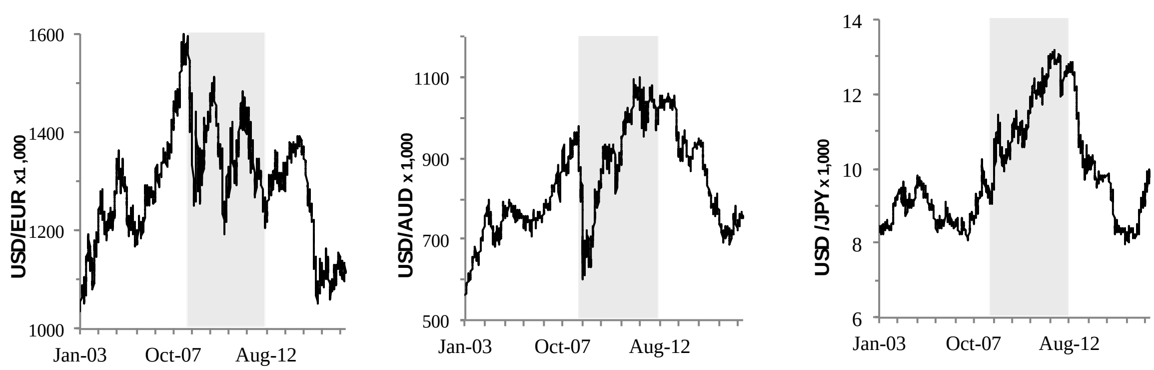
3.2. *Trends in currency markets*

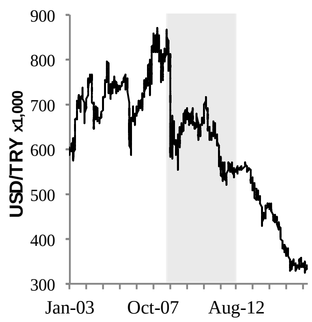
Figure 1 presents a subsample of three high- and three low-traded currencies against the US Dollar from January 1, 2003 to September 5, 2016. The period from the beginning of the sample until July 2008 features a general depreciation of the US dollar. However, the period from August 2008 to May 2012 is more difficult to characterize. Thus, while the US dollar was depreciating against AUS, JPY and BRL, it recorded various changes in terms of appreciation and depreciation against EUR, TRY and MXN. Caballero, Farhi, and

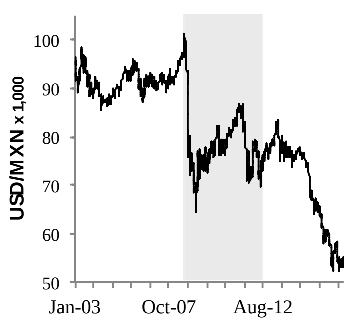
Gourinchas (2008) document a significant flow of capital across the global economy during this period, which helps to explain the turbulence observed. Basically, the subprime crisis created an abnormal demand for higher returns outside the main markets (i.e. in the emerging and commodity markets), which in turn fostered a higher demand for the foreign currencies of net-exporters of commodities. The last period in the sample – from June 2012 until September 2016 – was characterized by an appreciation of the US Dollar (although one exception to this pattern was Japan at the end of the sample). This US appreciation followed on from the events of the 2010 European debt crisis; the sharp fall in commodity prices at the end of 2011, and the crises faced by such countries as Greece (May 2010), Ireland (November 2010), and Portugal (May 2011), which subsequently escalated to affect Cyprus (December 2011) and Spain (July 2012). The final years in the sample were also characterized by the progressive recovery of the US economy.

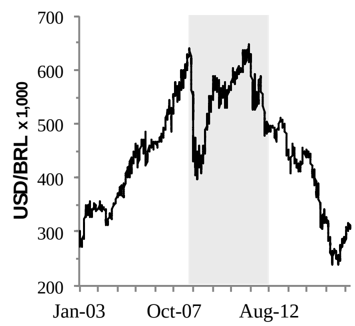
This raw characterization, which identifies the depreciation of the US Dollar from 2003 to 2007, a period of turbulence from 2008 to 2012, and a period of appreciation from 2013 onwards, also provides a reasonable fit with the behavior of the other exchange rates in our sample, but that are not included in the plot. We use this characterization below to describe some of our results.

Figure 1. Subsample of three high- and three low-traded currencies against US Dollar. The figure illustrates the behavior of the exchange rates in both mature (top row) and emerging (bottom row) economies. The period from the beginning of the sample until July 2008 is characterized, in general, by the depreciation of the US dollar (the Mexican Peso being an exception). The period from August 2008 to May 2012 is difficult to characterize, while the US dollar was depreciating against AUS, JPY and BRL, it recorded marked changes against EUR, TRY and MXN. As such, it can be labelled as a period of turbulence. Finally, from June 2012 until the end of the sample in September 2016, there was a general appreciation of the US Dollar (with Japan being one exception at the end of the sample). This characterization also fits reasonably well with the behavior of the other exchange rates in our sample. Our data span January 1, 2003- September 5, 2016.









4. Results

We organize our results in four sections. First, we describe the variance-decomposition exercise using the full sample, and both the log-volatility and log-quantile statistics. Second, we present our systemic index of financial fragility in global currency markets, and we compare it with a more traditional index based on volatility spillovers, similar to that proposed by Diebold and Yilmaz (2015), which is updated regularly on their web page[5]. Third, in seeking to emphasize the differences between volatility and tail spillovers, we analyze two recent, relevant dates in the global currency market in terms of financial stability using graphical network representations. Finally, we show how turnover as a measure of liquidity helps us understand the way in which currency shocks propagate in the market.

4.1. *Static variance decomposition of currency shocks: volatilities versus left tails*

In Tables 3 and 4, we show the 10-day-ahead variance decomposition of our two specifications. The currencies are organized from left to right (and from top to bottom) according to their turnover. The greatest turnover in the sample is displayed by the Euro-USD pair (EUR/USD), 31.3% of the total, while the lowest turnover is associated with the Philippine Peso (PHP), 0.1% of the total, according to the Bank of International Settlements (2016). This exercise is useful for identifying currencies with a high capacity to destabilize global currency markets, by generating significant shocks to the rest of the system. It also allows us to identify the most vulnerable currency pairs in our sample.

Several common patterns emerge from a comparison of the two tables. For example, the least liquid currencies in the sample are neither important transmitters nor receivers in absolute terms. COP, THB and PHP display the greatest percentage of variability arising from their own shocks, both in terms of volatility and depreciation-VaRs. Other currencies, while more liquid, present evidence of a similar behavior. This is the case of INR (especially in volatilities). None of these markets transmits (receives) a shock to (from) any other market above 7.0%[6].

[5] http://financialconnectedness.org/FX.html.

[6] 7% is approximately the 90th percentile in both the volatility- and VaR spillover tables.

Table 3. Volatility spillovers between the most traded free-floating currencies in the exchange rate market. The market that transmits the shock is shown in the columns, while the market that receives it is shown in the rows. Our sample runs from December 17, 2003 to September 5, 2016. The forecasting horizon was set at 10 days, and we used two lags in the case of volatility and one lag in the case of quantiles (following the BIC criterion). The *ij-th* entry is the estimated contribution to the forecast error variance of market *i* coming from innovations to market *j* (see equation (8)). The diagonal elements ($i=j$) represent the own-market spillovers while the off-diagonal elements ($i\neq j$) measure the pairwise volatility directional spillovers. In addition, the column labeled "all to i" (see equation (10)) report the total volatility spillovers 'to' (received by) each market from the rest of the system and the row labeled "i to all" (see equation (11)) report the total volatility spillovers 'from' (transmitted by) each market to the rest of the system. The total volatility spillover index defined in equation (9) is given on the bottom-right corner, and it is expressed in percentage points.

	EUR	**JPY**	**GBP**	**AUD**	**CAD**	**CHF**	**SEK**	**MXN**	**NZD**	**SGD**	**NOK**	**KRW**	**TRY**	**INR**	**BRL**	**ZAR**	**PLN**	**THB**	**COP**	**PHP**	**all to i**
EUR	18.3	3.1	6.9	6.1	4.3	12.1	10.0	3.2	4.5	3.9	9.0	2.0	1.9	0.1	1.6	2.5	8.5	0.3	1.2	0.6	**81.7**
JPY	5.4	33.5	6.5	6.9	3.8	5.5	4.1	2.6	6.2	3.0	4.2	3.0	2.5	0.1	1.4	3.5	4.0	0.8	2.0	1.0	**66.5**
GBP	8.8	5.1	22.0	7.3	5.8	6.3	6.9	3.4	6.0	3.1	7.0	2.6	2.1	0.0	1.5	3.3	6.1	0.2	1.9	0.5	**78.0**
AUD	6.0	4.4	5.8	18.8	6.8	4.3	5.3	4.5	10.2	4.5	6.0	3.4	3.3	0.3	3.0	4.0	5.2	0.6	2.5	1.1	**81.2**
CAD	5.7	3.5	6.6	9.4	22.4	4.5	5.4	3.4	6.6	3.8	5.9	3.1	3.2	0.1	2.7	4.1	5.6	0.4	2.8	0.7	**77.6**
CHF	15.0	4.0	6.3	5.4	4.2	22.6	8.8	2.2	4.0	3.7	7.8	1.5	1.8	0.1	1.1	2.6	6.8	0.5	1.1	0.5	**77.4**
SEK	11.2	2.9	5.8	6.2	4.6	8.0	18.9	4.2	4.6	3.2	10.0	3.1	2.0	0.4	1.5	2.5	8.5	0.4	1.2	0.8	**81.1**
MXN	3.8	2.4	3.4	5.4	2.9	2.0	4.4	32.2	4.1	4.4	4.1	5.9	3.2	2.5	4.7	3.6	6.1	0.2	3.1	1.4	**67.8**
NZD	5.6	4.9	6.0	12.7	5.8	4.1	5.0	4.0	19.3	3.9	5.5	3.2	3.5	0.1	3.1	3.9	5.0	0.9	2.3	1.2	**80.7**
SGD	6.1	2.8	4.1	7.2	4.4	4.7	4.5	5.2	4.9	22.1	5.1	6.5	3.0	1.1	2.8	3.5	5.5	1.9	2.8	1.7	**77.9**
NOK	10.2	2.9	6.2	6.8	5.1	7.3	10.3	4.1	5.0	3.7	18.2	3.1	2.3	0.2	2.0	2.8	6.8	0.5	1.9	0.7	**81.8**
KRW	2.8	2.8	2.9	4.2	2.9	1.6	3.6	5.9	3.0	4.9	3.4	40.1	2.1	2.3	3.5	1.1	3.7	1.1	4.4	3.7	**59.9**
TRY	2.9	2.7	2.4	4.9	3.8	2.3	2.6	4.0	4.0	2.8	3.1	2.9	42.9	0.4	4.3	5.1	4.0	1.5	2.6	0.8	**57.1**
INR	0.2	0.6	0.1	0.7	0.1	0.2	1.1	3.6	0.4	1.7	0.5	4.4	0.3	77.4	0.7	0.1	0.3	2.1	1.4	4.4	**22.6**
BRL	2.3	1.8	2.0	4.4	2.9	1.3	1.8	5.7	3.9	2.7	2.5	4.8	3.9	0.7	47.8	1.8	2.0	0.4	5.3	2.0	**52.2**
ZAR	4.5	3.5	5.0	7.4	5.6	3.8	3.9	5.2	5.7	3.8	4.5	1.7	5.5	0.4	2.6	28.4	5.5	0.7	1.9	0.5	**71.6**
PLN	9.6	2.8	5.4	5.8	4.5	6.3	8.3	5.3	4.5	3.9	6.7	3.2	2.7	0.1	1.6	3.7	23.2	0.4	1.2	0.8	**76.8**
THB	0.8	1.4	0.6	1.3	0.5	0.8	0.9	0.5	1.5	2.9	1.1	2.3	1.7	2.1	0.3	0.9	0.9	75.1	1.8	2.6	**24.9**
COP	0.9	1.0	1.2	2.0	2.2	0.7	0.8	2.1	1.7	1.7	1.2	4.2	1.6	0.8	3.3	0.9	0.9	1.1	70.6	1.2	**29.4**
PHP	1.0	1.4	0.7	2.1	1.2	0.7	1.3	1.9	1.8	2.3	1.0	7.0	1.6	5.1	2.7	0.5	1.5	3.5	2.6	60.2	**39.8**
Total	**121.4**	**87.5**	**99.8**	**125.0**	**93.7**	**98.9**	**108.0**	**103.2**	**101.9**	**85.9**	**107.0**	**107.9**	**91.0**	**94.4**	**92.1**	**78.9**	**110.0**	**92.5**	**114.5**	**86.5**	
i to all	**103.0**	**54.0**	**77.8**	**106.2**	**71.3**	**76.3**	**89.1**	**71.0**	**82.6**	**63.8**	**88.7**	**67.9**	**48.1**	**17.1**	**44.2**	**50.5**	**86.8**	**17.4**	**43.8**	**26.3**	**64.3**

Table 4. VaR spillovers between the most traded free-floating currencies in the exchange rate market. The market that transmits the shock is shown in the columns, while the market that receives it is shown in the rows. Our sample runs from December 17, 2003 to September 5, 2016. The forecasting horizon was set at 10 days, and we used two lags in the case of volatility and one lag in the case of quantiles (following the BIC criterion). The *ij-th* entry is the estimated contribution to the forecast error variance of market *i* coming from innovations to market *j* (see equation (8)). The diagonal elements ($i=j$) represent the own-market spillovers while the off-diagonal elements ($i \neq j$) measure the pairwise VaR directional spillovers. In addition, the column labeled "all to i" (see equation (10)) report the total VaR spillovers 'to' (received by) each market from the rest of the system and the row labeled "i to all" (see equation (11)) report the total VaR spillovers 'from' (transmitted by) each market to the rest of the system. The total VaR spillover index defined in equation (9) is given on the bottom-right corner, and it is expressed in percentage points.

	EUR	**JPY**	**GBP**	**AUD**	**CAD**	**CHF**	**SEK**	**MXN**	**NZD**	**SGD**	**NOK**	**KRW**	**TRY**	**INR**	**BRL**	**ZAR**	**PLN**	**THB**	**COP**	**PHP**	**all to i**
EUR	17.6	1.2	4.5	5.4	3.2	2.5	9.5	3.1	3.4	2.4	9.2	2.5	6.1	0.3	3.0	4.6	19.6	0.6	1.0	0.4	**82.4**
JPY	1.0	56.0	2.6	4.8	2.1	3.0	0.9	3.5	4.0	0.7	1.5	4.0	3.6	0.9	1.8	2.9	2.1	1.7	1.7	1.2	**44.0**
GBP	5.4	2.9	28.9	7.0	4.2	0.9	4.3	3.5	5.0	2.6	5.3	4.4	4.9	0.5	1.8	6.5	9.2	0.6	1.6	0.4	**71.1**
AUD	2.2	2.0	2.1	24.6	5.0	0.2	2.7	5.5	9.5	2.8	3.1	5.2	9.2	1.6	4.8	7.4	6.9	1.2	2.6	1.4	**75.4**
CAD	1.6	1.3	2.1	8.8	34.9	0.6	2.2	6.4	4.8	1.7	3.1	4.2	5.8	0.3	4.4	5.7	5.4	1.5	3.9	1.2	**65.1**
CHF	6.6	9.5	1.8	0.5	2.0	67.3	1.7	0.9	1.3	0.0	4.1	0.1	0.0	0.2	0.6	0.1	2.3	0.8	0.1	0.0	**32.7**
SEK	9.0	1.3	3.3	6.7	3.6	0.8	16.4	4.8	3.3	2.4	9.2	3.2	8.2	0.6	3.4	5.6	16.3	0.5	1.1	0.6	**83.6**
MXN	1.0	1.0	0.8	4.7	2.4	0.2	1.6	39.6	2.3	1.9	1.6	3.4	10.8	1.3	8.0	7.9	6.1	1.0	3.9	0.6	**60.4**
NZD	2.3	2.2	2.3	14.9	3.9	0.2	2.6	4.8	23.5	2.6	3.0	4.7	8.6	0.9	4.6	6.7	6.9	1.4	2.6	1.4	**76.5**
SGD	1.7	0.7	1.3	5.0	1.5	0.2	1.4	4.1	2.9	38.8	1.9	11.1	5.0	3.6	2.7	3.5	6.0	4.3	2.1	1.9	**61.2**
NOK	7.0	1.4	3.6	6.7	4.1	1.3	7.9	4.4	3.8	2.5	22.0	3.1	6.2	0.9	4.2	5.5	12.0	0.9	1.7	0.7	**78.0**
KRW	1.0	0.9	1.0	4.7	1.7	0.0	1.4	2.9	2.1	6.2	1.8	45.7	8.1	4.1	2.9	3.6	5.2	2.0	2.4	2.1	**54.3**
TRY	1.0	0.7	0.7	4.4	1.5	0.1	1.6	5.7	2.0	2.2	1.5	4.4	50.8	1.3	4.4	7.4	5.7	0.8	2.7	1.3	**49.2**
INR	0.2	0.7	0.2	2.0	0.2	0.0	0.5	2.1	1.0	2.6	0.4	3.6	3.3	73.2	2.0	1.7	1.7	1.4	1.6	1.6	**26.8**
BRL	0.5	1.1	0.3	3.8	2.0	0.0	0.8	7.2	2.2	1.5	0.7	3.9	9.0	1.2	52.4	4.7	2.4	0.9	4.6	0.7	**47.6**
ZAR	1.4	1.2	1.5	6.9	2.8	0.2	2.0	8.0	3.3	2.2	1.7	4.0	13.1	0.6	5.4	34.5	6.3	1.3	2.7	0.8	**65.5**
PLN	5.9	0.5	2.4	5.1	2.5	0.5	5.1	5.8	2.9	2.5	4.1	3.8	9.3	1.2	3.3	6.2	35.7	0.9	1.3	1.0	**64.3**
THB	0.2	0.2	0.3	1.1	0.7	0.1	0.2	0.6	0.9	1.6	0.6	1.5	0.3	1.4	0.3	0.7	1.1	86.0	0.6	1.5	**14.0**
COP	0.2	0.4	0.4	1.0	1.5	0.0	0.4	3.0	0.9	1.7	0.4	2.9	4.5	1.6	3.7	2.1	1.3	0.9	72.3	0.6	**27.7**
PHP	0.4	0.3	0.4	2.7	1.6	0.0	0.6	1.6	1.7	3.0	0.7	6.1	4.0	4.2	1.9	2.0	2.5	5.9	1.9	58.5	**41.5**
Total	**66.5**	**85.5**	**60.4**	**120.8**	**81.2**	**78.2**	**63.8**	**117.8**	**80.7**	**82.0**	**75.8**	**122.0**	**170.9**	**99.7**	**115.6**	**119.4**	**154.9**	**114.6**	**112.2**	**78.1**	
i to all	**48.8**	**29.5**	**31.5**	**96.2**	**46.3**	**10.8**	**47.4**	**78.1**	**57.2**	**43.2**	**53.9**	**76.2**	**120.1**	**26.6**	**63.2**	**84.8**	**119.2**	**28.6**	**39.9**	**19.6**	**56.1**

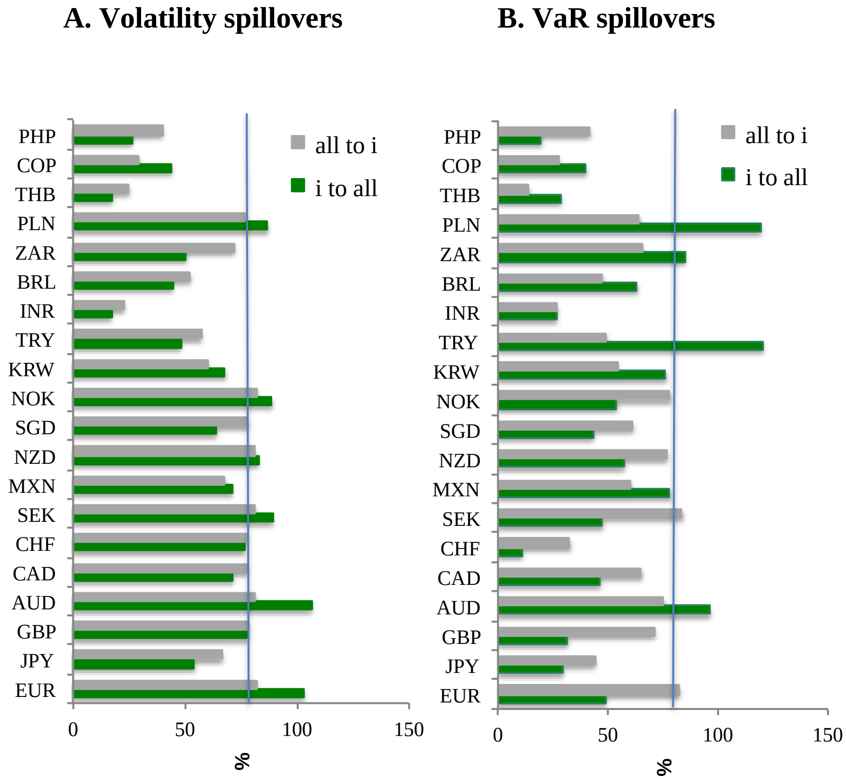
The most liquid currencies in our sample also tend to be more integrated with the rest of the system, rarely displaying a number above 50% along their main diagonal, with the exceptions of JPY and CHF in the depreciation tails. In the case of these last two currencies, an interesting finding is highlighted by comparing the two tables: in terms of volatility spillovers, the amount of variation explained by their own shocks is below 50%, but this increases for the left tail VaRs. This means that these currencies tend to receive fewer shocks from the other markets on the depreciation tail than they do in their volatility. Moreover, due to the symmetric nature of volatility, this might also signal that they are more prone to receive shocks on the right tail (appreciation) than they are on the left. This behavior is expected, because as *haven* currencies, the central banks in these countries are generally more concerned about episodes of strong appreciation than they are about depreciations, given that they are more sensitive on the appreciation tail of their distributions.

The Euro provides us with a notorious example of asymmetry when we compare the linkages in the left tail of the distribution with those involving volatility. While in the latter case the Euro transmits shocks above 7.0% on the markets of United Kingdom (8.8%) Switzerland (15%), Sweden (11.2%), Norway (10.2%) and Poland (9.6%), the shocks transmitted by the Euro on these markets are considerably smaller in magnitude in the left tail, and only equal or above 7.0% in the cases of Sweden (9%) and Norway (7%). Note that this should not necessarily be the case because by construction the FEVDs are normalized; thus, they are directly comparable in volatilities and quantiles. What it provides evidence of is the asymmetric nature of the propagation of shocks.

Figure 2 complements the analysis by showing the sums of the rows and columns presented in Tables 3 and 4. That is, it shows the total spillovers from each market to the rest of the system, and from the rest of the system to each market, in volatility (Panel A) and depreciation-VaR (Panel B). It is now readily apparent that the most vulnerable currencies in terms of volatility (let's say with above 80% of their shocks being explained by other markets) are the Euro, the two Nordic currencies in the sample (NOK, SEK), and the New Zealander (NZD) and Australian (AUD) dollars. While only the Euro and the Swedish Krone (SEK) are equally prone to receiving shocks in the depreciation tail above the 80% threshold.

Yet, a comparison of the two figures does not allow us to establish whether, in general, the shocks propagate more in the left tail or in the volatilities, given that for some markets volatility shocks dominate, while for others quantile shocks dominate. Important asymmetries are found, for example, in the markets of South Africa (ZAR) and Turkey (TRY). These markets change from net-receivers of volatility to net-transmitters of shocks in the left tail. Once again, this points to the asymmetric nature of their reactions to international FX spillovers. In general, after comparing Panels A and B in Figure 2, the analysis of JPY and CHF conducted above is confirmed.

Figure 2. Total spillovers (static) during the sample period. The figure shows the sum of the rows and columns in Tables 3 and 4. That is, it shows the total spillovers from each market to the rest of the markets, and from the rest of the markets to each market, in volatility (Panel A) and depreciation-VaR (Panel B). The estimation sample runs from January 1, 2003 to September 5, 2016.



4.2. *Total volatility and VaR spillover indices*

The static analysis reveals some interesting results but it is based on fixed parameters and, therefore, is not helpful in understanding how spillovers change over time. In order to assess the time-varying nature of spillovers, we estimate the model using a 250-day rolling window and a 10-day predictive horizon for the underlying variance decomposition[10]. Figure 3 shows the total volatility and quantile indices from December 17, 2003 to September 5, 2016[11].

The two systemic measures tend to co-move during the sample period, showing an increasing trend until 2012. However, while the volatility spillover index is lower than the quantile spillover index until 2012, this situation is reversed from 2012 onwards, coinciding with a huge reduction in quantile spillovers. Interestingly this reduction coincides with a

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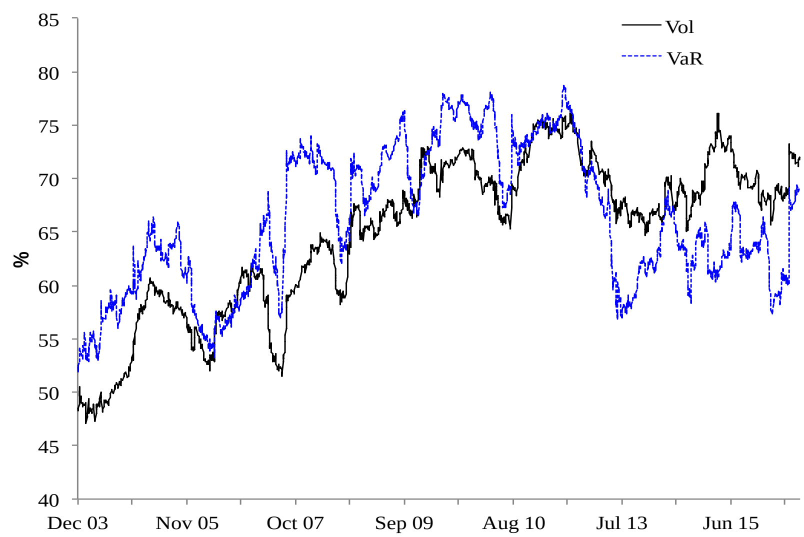
[10] Our main results are not sensitive to realistic changes in the window length and the forecasting horizon. We adhered to the most frequent settings in the extant literature, see for example Greenwood-Nimmo et al., (2016).

[11] One advantage of analyzing spillovers following the proposal of Diebold and Yilmaz (2009, 2012) is that the dynamic cross-spillovers statistics (both total and pairwise) are robust to structural shifts in the location parameters of the exchange rates, which are evident, for instance, from visual inspection of Figure 1.

reduction in the volume traded in FX markets[12]. It seems that extreme cross-market shocks are positively related to the total market turnover. This is important because, as shown by Mancini et al. (2013), liquidity in the foreign exchange market is not as stable as previously thought and it can foster financial crises in other markets of significant magnitudes.

Figure 3: Total Volatility and VaR spillover indices. The figure shows the total (dynamic) indices based on volatility- and VaR-statistics for the full sample, which runs from December 17, 2003 to September 5, 2016 (the first observations were lost in the estimation process). The estimations were performed using rolling windows of 250 observations, forecasting horizon of 10 days, and two lags in the case of volatility and one lag in the case of VaR-statistics (following the BIC criterion). The VaR were constructed using an asymmetric CAViaR model that allows the two tails of the FX distribution to be treated differently.



Meteor showers (cross-spillovers) were more important during the subprime crisis and its aftermath than during the rest of the sample, this finding only being evident when we focus on the quantile index. This means the volatility spillover index underestimated the impact of cross-spillovers by as many as 1,000 basis points (bp) in the year following the subprime crisis (July 2007 – August 2008) and by almost 500 bp during the European debt crisis in 2010. Since then the volatility spillover index has consistently overestimated the effect of meteor showers on the global FX market.

Furthermore, the quantile-based index seems more sensitive than the volatility-based index to events that impacted global currency markets, including the escalation in the Russian and

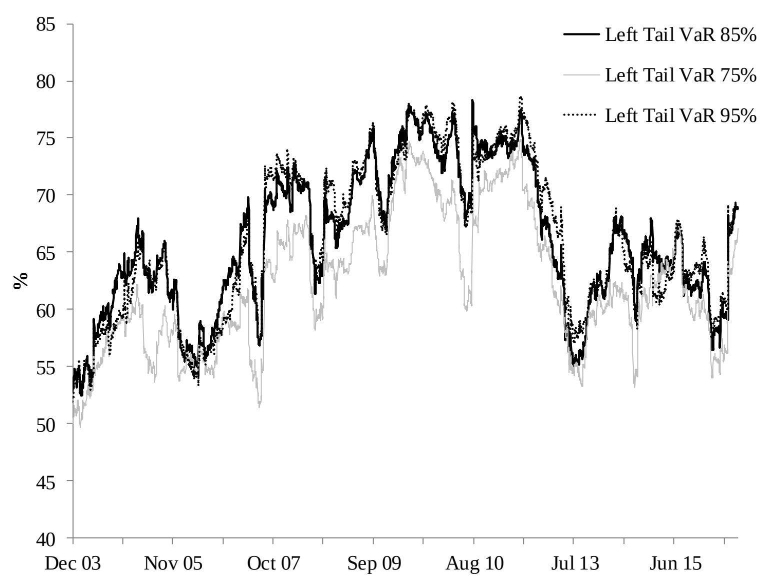
[12] Daily FX market volumes fell from 5.4 to 5.1 trillion dollars between 2013 and 2016. Prior to 2013, the FX market witnessed an unstoppable year-on-year increment, accumulating an increment of 61% between 2007 and 2013 (Bank of International Settlements, 2016). We tested for the statistical significance of the relationship between the cross-spillover indices and the FED-funds rate, the illiquidity index by Mancini et al. (2013), the TED spread and the trade index of the US economy, respectively. These variables display always a p-value bellow 0.05, which makes us confident about the relationships emphasized in the main text. We tried several specifications in our regression exercises, which are available upon request.

Ukrainian conflict in 2014, the Greek referendum in June 2015, and Brexit in June 2016. The reduction of risk shown by the quantile-based index is also consistent with the recovery experienced by the US economy towards the end of the sample. The demand for US dollars and the lower demand for foreign currencies may explain the reduction in cross-spillovers between commodities and emerging market currencies during the period 2012-2016.

To test whether the two indices are indeed statistically different, we calculated a Kolmogorov-Smirnov (KS) statistic as 0.12. In this case the null of homogeneity (the two series were drawn from the same distribution) is rejected at 99% confidence level. We also regressed the quantile-spillover index on the volatility-spillover index. We estimated the partial correlation between the two series on 0.72, the Pearson's correlation on 0.67 and the coefficient of determination equal to 0.45. This means that half of the variation of the quantile spillover statistic is not captured by the variations in the volatility-based index. By construction, this unexplained variation is related to depreciation-scenarios unmatched by similar movements in the appreciation tail of the currency returns distributions.[13]

As a robustness exercise, we changed the quantile used to estimate our depreciation spillover statistic. On top of the depreciation-VaR at 95% of confidence we also present in Figure 4 the results related to the 85% and 75% levels of confidence. As can be observed the main dynamics of the index does not change considerably, and naturally the lower the confidence level the lower the cross-spillover, which also highlight the importance of considering extreme depreciations when monitoring the market, as it is done by our index.

Figure 4: Total cross-spillover index: quantile sensitivity. The figure presents the cross-spillover index changing the quantile of interest between the VaR calculated at 75% and the 95% of confidence level.



[13] We also estimated a DCC-GARCH (1,1) model and an alternative cross-volatility index based on this GARCH specification. The KS statistic, once again, allows us to reject the null of equality of the distribution of the two indices.

Finally, we explored up to what extent common factors related to the US market (our benchmark for the currency pairs construction) explain the dynamics of the depreciation spillovers. To this end we regressed our quantile-based spillover statistic against the following variables: The NBER recession indicator, the shadow rates of the effective federal funds proposed by Wu and Xia (2016), TED spreads, and the illiquidity index for currency markets (US as a benchmark) proposed by Karnaukh et al. (2015).

Overall, our results, reported in Table A3 of the Appendix, conclude that the US market factors are drivers of currency quantile-based spillovers around the world. However, a model that considers all the factors simultaneously (Model 5) explains only around 14% of the variability of the quantile-based spillovers index (when only some of the factors are included, the coefficient of determination ranges between 0.01 and 0.09). The coefficient associated to the NBER recession indicator displays a positive sign in Model 1 (when it is significant). This means that a recession is associated with an increase in the cross-spillovers between the exchange rates. The demand of USD dollars and the capital inflows to the US market depend on the current state of the US economy. In the presence of a severe recession, the inflow of capital generates a general appreciation of the US foreign exchange rate that is transmitted to all currency markets (in the form of depreciations). It seems that this effect is more pronounced during recessionary periods, than during expansionary phases, when international capitals dynamics of flight to quality take place, paradoxically, increasing the exposure to the US market, which nevertheless is considered in these cases as the safest market in the world. Liquidity is related to the capacity of absorption of shocks by the global currency market. Illiquid scenarios as indicated by an increment of the illiquidity measure by Karnaukh et al. (2015) (Models 2, 5) are associated with larger cross-spillovers in the depreciation quantiles and consequently to a higher systemic risk in currency markets. Finally, the shadow rate of the FED funds is negatively associated with the cross-spillover index. That is, a reduction in the US interest rate is associated with an increase in depreciation-spillovers around the world, as it is generally related to bad economic conditions in the global markets, which induce international portfolio rebalancing against most currency markets, especially emerging economies, and therefore a generalized depreciation. When all the variables are incorporated into the regression results as in Model 5, only the liquidity measure and the US interest rate remain significant.

4.3. *Network analysis of two dates: subprime and Brexit*

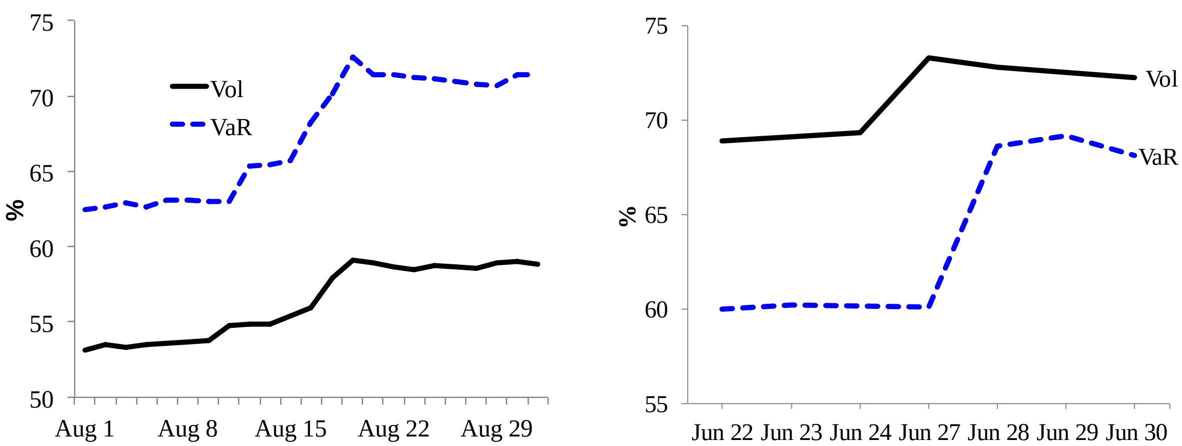
Next we analyze some of the asymmetries in the propagation of shocks which can be observed when comparing net-spillovers on specific dates that were important for the FX market in terms of financial stability. In Figure 5, we plot the indices' dynamics before and after two major events in the global currency markets. Panel A shows both measures in the period around the subprime crisis – from August 1 to August 31, 2007[14], and Panel B shows the measures before and after the Brexit vote, held on June 23, 2016. Both were largely unexpected events with significant consequences for carry trade strategies and for the strength of the British Pound and other currencies, respectively. As can be observed,

[14] Melvin and Taylor (2009) pin the origin of the FX crisis to August 16, 2007, when a major unwinding of carry trade occurred and many currency investors suffered huge losses.

before August 16 the two systemic-currency indices, based on volatility and on left-tail-VaR statistics, displayed similar dynamics. Cross-spillovers accounted for around 53% of the total variation in the exchange rate markets according to the volatility index, and around 63% according to the VaR index. After August 16, the date identified by Melvin and Taylor (2009) as marking the onset of the crisis in the FX market, cross-spillovers rose to 59.12%, according to the volatility index, and remained at this level over the following days, while the increment was of 963 bp from 63 to 72.63%, according to the VaR index. The Brexit vote provides another significant example. While the volatility index (which was roughly 1,000 bp above the VaR-index during this episode) increased from 69.32% on June 24 to 72.82% on June 28 (350 bp), between the same dates the VaR index increased from 60.10% to 68.63% and remained at this level thereafter (that is, 853 bp above its initial magnitude).

Figure 5: Total Volatility and VaR spillovers on two dates. The figure shows the two indices, based on volatility- and depreciation-VaR, during two turbulent episodes faced by the exchange rate market: the aftermath of the subprime crisis and the days immediately before and after the Brexit vote. The two statistics display different sensitiveness to these events. The plot was constructed after estimating volatility and VaRs using 20 series of the most traded floating currencies in our sample.

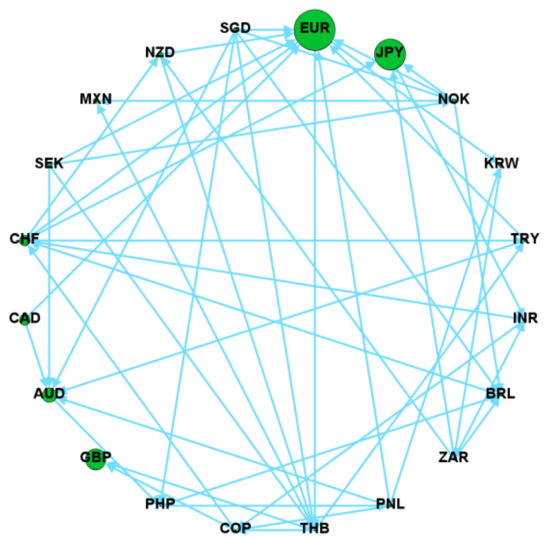
A. August 1 to August 31 – 2007 **B. June 22 to June 30 – 2016**



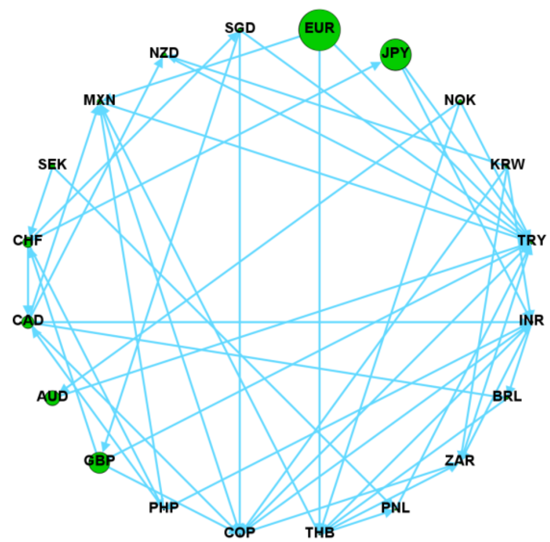
These significant differences have a critical impact on financial stability and need to be taken into consideration when conducting exercises that seek to monitor financial fragility around the world and when designing enhanced hedging mechanisms for international investors.

Figure 6 shows the graphical network representation of the volatility and quantile spillovers for the two periods analyzed above. The nodes represent each currency pair and their respective sizes are given by the turnover of each market, while the direction of the edges is given by the sign of the net pairwise spillover. We have plotted two dates: August 20, 2007, at the beginning of the global financial crisis and June 28, 2016, just after the Brexit vote. For the sake of clarity, we have only plotted the highest spillovers (above the 75th percentile) for each date.

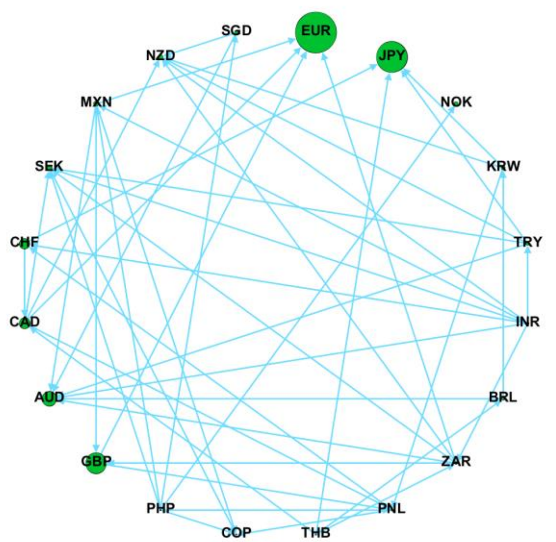
Figure 6: Net volatility and quantile spillovers on selected dates. The figure shows the net-volatility (left) and depreciation (right) spillovers among the 20 markets in our sample for two selected dates August 20, 2007 (subprime FX crash) and June 28, 2016 (Brexit). We only plot the highest 25% spillovers for each date. The size of each node is given by the turnover of each market in 2016.



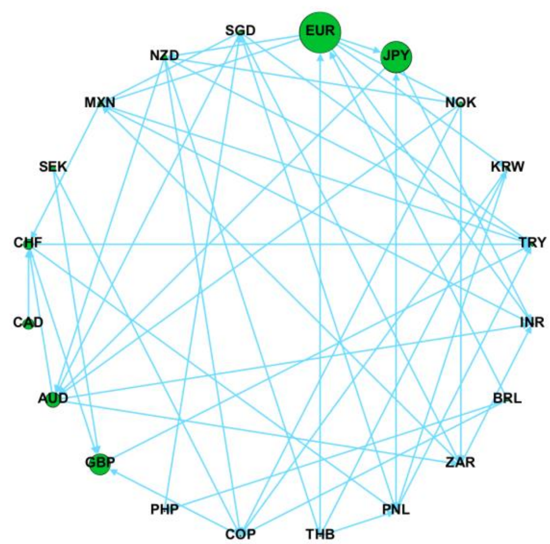
(a) 20 August 2007: net-volatility spillovers



(b) 20 August 2007: net-quantile spillovers



(c) 28 June 2016: net-volatility spillovers



(d) 28 June 2016: net-quantile spillovers

Panel (a) presents the pairwise spillovers in volatilities for August 20, 2007. It shows that the Euro, Yen, Swiss Franc, and to a lesser extent other liquid currencies such as the Australian Dollar, were the main receivers of shocks. In contrast, if we focus on panel (b), which shows the net pairwise spillovers across quantiles, it is Turkey and the other emerging markets that received most of the shocks. We believe that these outcomes reflect the fact that the subprime crisis led to massive flows of capital and the reallocation of carry-trade portfolios, which experienced considerable losses. This process primarily affected strong currencies, such as the Euro and Yen, in the right tail of their distributions (appreciations), but it also affected weaker currencies, such as the Turkish Lira, in their left tails. In terms of financial stability, it is necessary to understand these phenomena and to monitor not only the appreciation pressures of strong currencies, but also (and we would add mainly) the depreciation pressures faced by weaker currencies, which all told are more likely to have to face currency crises.

A similar analysis can be conducted in the wake of the Brexit vote. Clearly, the net receivers of volatility shocks were the commodity currencies and strong currencies, in other words the currencies associated with more developed markets. Nevertheless, panel (d) shows that other currencies, including the South African Rand, the Turkish Lira and the Indian Rupiah, were also affected in the left tail of their distributions. Naturally, some currencies, including the Euro and Swiss Franc, were affected regardless of the measure, because the quantiles are not independent of the variances. Surprisingly, the British Pound only received *net*-shocks in volatility from Poland and Mexico, and in the quantiles from Switzerland, Sweden and Colombia. The impact recorded by the currencies of the eastern European countries is as expected, given that they are directly affected by the variations suffered by the Euro market.

4.4 Turnover, liquidity and spillovers

Finally, we are also interested in analyzing how traded volume helps us understand the patterns of global volatility and VaR spillovers in the FX market. Figure 7 shows the net-volatility spillovers among the quartiles of the currencies in our sample, sorted according to traded volume in 2016[15]. The analysis runs from December 17, 2003 to September 5, 2016. The first quartile corresponds to the most traded currencies, while the last quartile groups the least traded currencies. The traded volume is as reported in the Bank of International Settlements (2016). The group in the column is the one that transmits the shock while the group in the row is the one that receives it.

Our intuition based on the literature on exchange rate fundamentals rooted in market microstructures, as in Evans (2011), is that, rather than macro-fundamentals, liquidity matters for spillovers. Thus, world currency spillovers should behave differently according to how much investors trade them. Indeed, we are able to document that this is in fact the case. In general, if we divide our sample into three periods – corresponding roughly to US dollar depreciation (from January 2003 to June 2008), market turbulence without any clear trend in the US dollar series (from July 2008 to May 2012), and US dollar appreciation (from June 2012 to September 2016, when our sample ends)[16] – we can document several trends. As far as volatility spillovers are concerned (Figure 7), the least traded currencies (those in quartile 4) are almost always net-receivers of volatility shocks and, when they are transmitters, the net spillover is low. If we examine the currencies in quartiles 1, 2 and 3, we see that during the period of dollar depreciation there was no clear trend in the direction of net spillovers, but that they were relatively low. During turbulent times, the more liquid a currency was the more shocks it received from less liquid currencies. This behavior was

[15] Individual net volatility and VaR spillover measures are provided in Figures A1 and A2 of the appendix.

[16] See Figure 1.

reversed during the period of US dollar appreciation, when the more liquid a currency was the more shocks it transmitted to the rest of the markets.

Interestingly, the shocks propagate as in *a cascade*: the more liquid a set of currencies is the more likely *it affects* all the other currencies, *during depreciation periods* (against the USD). Conversely, the more liquid it is the more likely *it gets affected* by all the other currencies *during turbulent periods that lack a clear trend* in terms of appreciation or depreciation.

The situation is very different when we examine tail spillovers (Figure 8). Currencies in quartiles 1 and 2 (the most liquid) are, by rule, net-receivers, while those in quartiles 3 and 4 (the least liquid) are net-transmitters. This is very likely a consequence of the latter being considerably more exposed to downside risk in the global currency markets. Notice, in any case, that this is a net result and as such it is silent about the size of the shocks.

Figure 7: Net volatility spillovers among world currencies sorted according to traded volume. The figure shows net-volatility spillovers among the quartiles of the currencies in our sample, sorted according to traded volume in 2016. The first quartile corresponds to the most traded currencies, while the last quartile groups the least traded currencies. The traded volume is as reported in the Bank of International Settlements Triennial Report (BIS, 2016). The net pairwise volatility spillover index is given by $C_{ij}(H) = [(\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H))/N] \times 100$, see equation (13). The group in the column is the one that transmits the shock while the group in the row is the one that receives it. A positive number means that the group *i* (in the column) is a net transmitter of shocks to the group *j* (in the row) in this period, while a negative number means it is a net receiver. The estimations were performed using rolling windows of 250 observations and a forecasting horizon of 10 days.

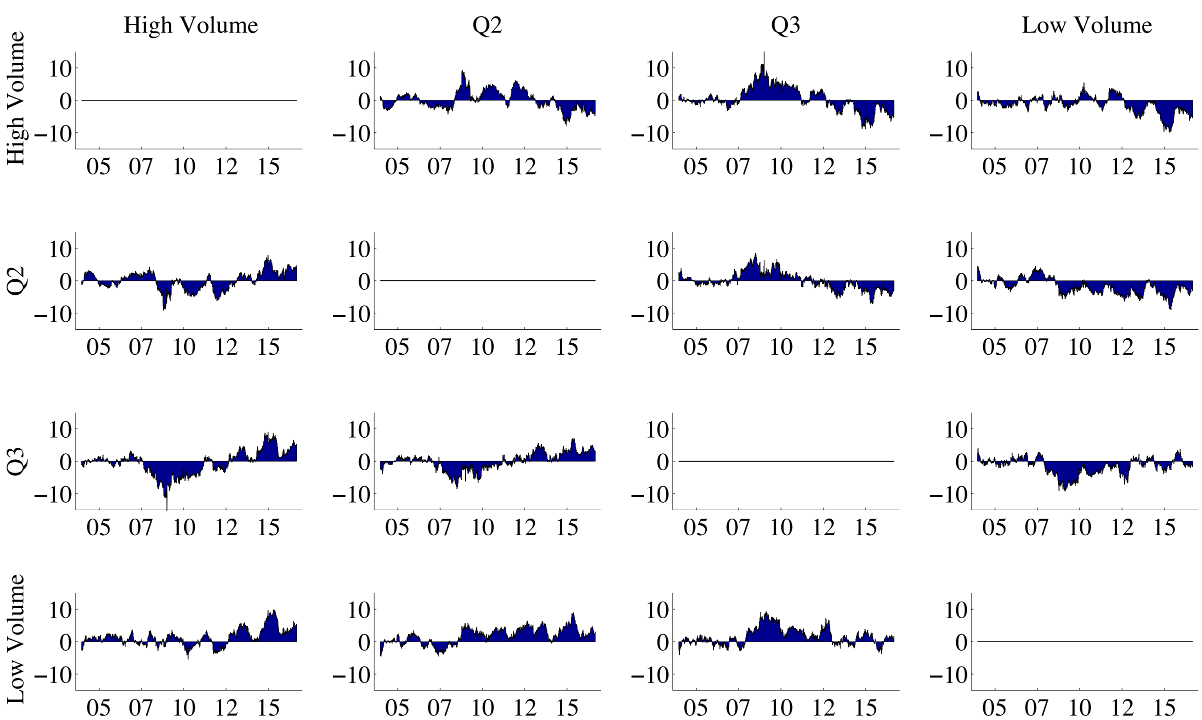
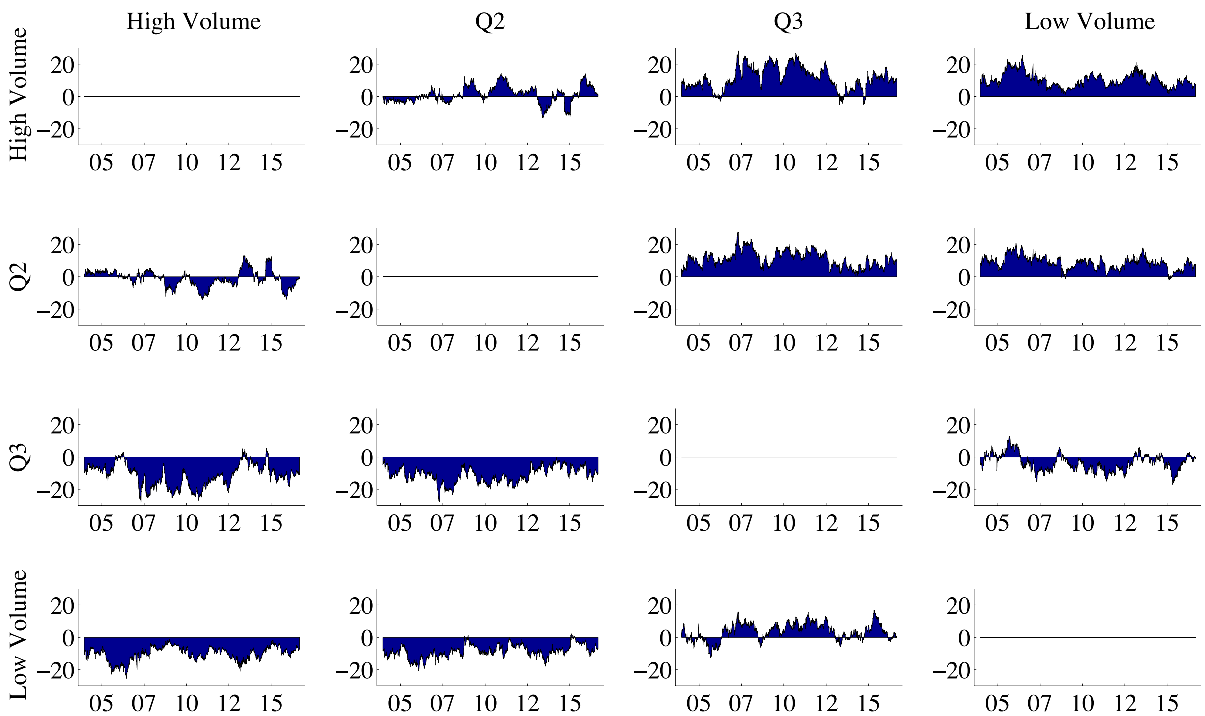


Figure 8: Net VaR spillovers among world currencies sorted according to traded volume. The figure shows the net-VaR spillovers among the quartiles of the currencies in our sample, sorted according to traded-volume in 2016. The first quartile corresponds to the most traded currencies, while the last quartile groups the least traded currencies. The traded volume is as reported in the Bank of International Settlements Triennial Report (BIS, 2016). The net pairwise VaR spillover index is given by $C_{ij}(H) = [(\tilde{\theta}_{ji}(H) - \tilde{\theta}_{ij}(H))/N] \times 100$, see equation (13). The group in the column is the one that transmits the shock while the group in the row is the one that receives it. A positive number means that the group *i* (in the column) is a net transmitter of shocks to the group *j* (in the row) in this period, while a negative number means it is a net receiver. The estimations were performed using rolling windows of 250 observations and a forecasting horizon of 10 days. The VaR were constructed using an asymmetric CAViaR model that allows the two tails in the distribution to be treated differently.



5. Conclusions

We estimate spillovers between volatilities and between downside risk VaRs (associated with depreciations) for 20 currencies of both mature and emerging FX markets. Our depreciation tail measure was constructed using a CAViaR model with asymmetric slopes that allows us to treat each tail of the daily variations in the FX market differently.

First, we find that risk measurement varies considerably depending on the part of the distribution targeted by the analysis. That is, the most vulnerable FX markets differ if we focus on the depreciation tail as opposed to on volatility. To document this, we analyzed recent events in the history of FX markets – specifically the subprime crash and the Brexit vote – by means of directional pairwise statistics and graphical networks.

Thus, we find that the least liquid currency markets tend to be more vulnerable and to transmit more shocks in the left tail of the distribution than is the case with volatility. This is fundamental for the correct assessment of systemic risk in currency markets and for monitoring financial fragility and distress in currency markets around the world. In keeping with this outcome, we construct an index of financial fragility based on cross-spillovers among the left tails of the distributions (depreciation episodes) and show that this index is much more sensitive than a traditional volatility index to such events as political upheavals and global crises.

Finally, for each currency in our sample, we employed turnover as a proxy for liquidity. This has helped us shed new light on the propagation mechanisms of currency shocks. We find that the most liquid currencies are generally net-transmitters of volatility during periods of US dollar appreciation, while the most liquid currencies are net-receivers of volatility in periods of turbulence lacking any clear trend. Similarly, the least liquid currencies almost always behave as net-receivers of volatility, rarely interacting with the rest of the systems, which shows their lack of integration in global financial markets.

In contrast, when we focus on tail spillovers corresponding to depreciation tails, the general perspective changes considerably. The most liquid currencies are almost always net-receivers of shocks, while those in the least liquid quartiles (3 and 4) are net-transmitters. This finding underlies the nature of the latter, which is considerably more exposed to downside risk in global currency markets than is the former. It also highlights the convenience of using a measure like the one proposed here, based on depreciation-quantiles, when assessing global financial stability conditions in FX markets.

Our main findings have important policy implications. Depreciation spillover is a concern for vulnerable economics such as emerging countries. Accumulating international reserves in this context seems as an optimal policy response for those countries highly susceptible to depreciation spillovers (particularly shock receivers). Such a strategy may alleviate the burden imposed by depreciation pressures, which is mainly related to the possibility of facing a currency crisis. The cumulated reserves send a signal to the markets indicating that the country will be prepared to lean against the wind when it comes to stabilize strong depreciation pressures. This process needs to be accompanied by a clear and systematic response on the side of monetary authorities, which indicate up to what extent they would pursue a stabilization policy when required to preserve the value of the domestic currency.

References

Alizadeh, S., Brandt, M.W., Diebold, F.X., 2002. Range-Based Estimation of Stochastic Volatility Models. J. Finance 57, 1047–1091. doi:10.1111/1540-6261.00454

Antonakakis, N., 2012. Exchange return co-movements and volatility spillovers before and after the introduction of euro. J. Int. Financ. Mark. Institutions Money 22, 1091–1109. doi:10.1016/j.intfin.2012.05.009

Apostolakis, G., Papadopoulos, A.P., 2015. Financial stress spillovers across the banking, securities and foreign exchange markets. J. Financ. Stab. 19, 1–21. doi:10.1016/j.jfs.2015.05.003

Baillie, R., Bollerslev, T., 1990. Intra-day and inter-market volatility in foreign exchange rates. Review of Economic Studies 58, 565-585.

Bank of International Settlements, 2016. Triennial Central Bank Survey of foreign exchange and OTC derivatives markets in 2016.

Barndorff-Nielsen, O.E., Kinnebrock, S., Shephard, N., 2010. Measuring Downside Risk – Realized Semivariance, in: Bollerslev, T., Russell, J., Watson, M.W. (Eds.), Volatility and Time Series Econometrics. Oxford University Press, Oxford, 117–136. doi:10.1093/acprof:oso/9780199549498.003.0007

Baruník, J., Kočenda, E., Vácha, L., 2017. Asymmetric volatility connectedness on the forex market. J. Int. Money Financ. 77, 39–56. https://doi.org/10.1016/j.jimonfin.2017.06.003

Bekaert G., Engstrom, E.G., Xu, N.R., 2017. The time variation in risk appetite and uncertainty, working paper Columbia Business School 17-108, available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3069078

Bekaert G., Hoerova, M., Lo-Duca, M., 2013. Risk, uncertainty and monetary policy. Journal of Monetary Economics. 60 (7), 771-788.

Bekiros, S.D., Diks, C.G.H., 2008. The nonlinear dynamic relationship of exchange rates: Parametric and nonparametric causality testing. J. Macroecon. 30, 1641–1650. doi:10.1016/j.jmacro.2008.04.001

Bubák, V., Kočenda, E., Žikeš, F., 2011. Volatility transmission in emerging European foreign exchange markets. J. Bank. Financ. 35, 2829–2841. doi:10.1016/j.jbankfin.2011.03.012

Caballero, R.J., Farhi, E., Gourinchas, P.-O., 2008. Financial Crash, Commodity Prices, and Global Imbalances. Brookings Pap. Econ. Act. 2008, 1–55. doi:10.1353/eca.0.0013

Cai, F., Howorka, E., Wongswan, J., 2008. Informational linkages across trading regions: Evidence from foreign exchange markets. J. Int. Money Financ. 27, 1215–1243. doi:10.1016/j.jimonfin.2007.08.001

Chen, Y., 2014. Understanding Exchange Rate Behaviour. Int. Financ. 17, 257–271. doi:10.1111/infi.12051

Corwin, S.A., Schultz, P., 2012. A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices. J. Finance 67, 719–760. doi:10.1111/j.1540-6261.2012.01729.x

Coudert, V., Couharde, C., Mignon, V., 2011. Exchange rate volatility across financial crises. Journal of Banking and Finance 35, 3010-3018.

Diebold, F.X., Yilmaz, K., 2009. Measuring Financial Asset Return and Volatility Spillovers, with Application to Global Equity Markets. Econ. J. 119, 158–171. doi:10.1111/j.1468-0297.2008.02208.x

Diebold, F.X., Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. Int. J. Forecast. 28, 57–66. doi:10.1016/j.ijforecast.2011.02.006

Diebold, F.X., Yilmaz, K., 2014. On the network topology of variance decompositions: Measuring the connectedness of financial firms. J. Econom. 182, 119–134. doi:10.1016/j.jeconom.2014.04.012

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

Engle, R.F., Ito, T., Lin, W-L., 1990. Meteor showers or heat waves? Heteroscedastic intra-daily volatility in the foreign exchange market. Econometrica 59, 525-542.

Engle, R.F., Manganelli, S., 2004. CAViaR: Conditional Autoregressive Value at Risk by Regression Quantiles. J. Bus. Econ. Stat. 22, 367–381. doi:10.1198/073500104000000370

Evans, M.D.D., 2011. The Microstructure of Currency Markets, in: Caprio, G., Montiel, P. (Eds.), The Encyclopedia of Financial Globalization. Elsevier, New York.

Galagedera, D.U., Kitamura, Y., 2012. Effect of exchange rate return on volatility spill-over across trading regions. Japan World Econ. 24 (4), 254–265.

Greenwood-Nimmo, M., Nguyen, V.H., Rafferty, B., 2016. Risk and return spillovers among the G10 currencies. J. Financ. Mark. 1–20. doi:10.1016/j.finmar.2016.05.001

Guiso, L., Sapienza, P., Zingales, L., 2017. Time varying risk aversión, working paper Chicago Booth June, available at http://faculty.chicagobooth.edu/luigi.zingales/papers/research/RiskAversion.pdf

Hogan, K.C., Melvin, M., 1994. Sources of meteor showers and heat waves in the foreign exchange market. Journal of International Economics 37, 239-247.

Hong, Y., 2001. A test for volatility spillover with application to exchange rates. J. Econom. 103, 183–224. doi:10.1016/S0304-4076(01)00043-4

International Monetary Fund, 2014. Annual Report on Exchange Arrangements and Exchange Restrictions.

Ito, T., Engle, R.F., Lin, W.L., 1992. Where does the meteor shower come from? The role of stochastic policy coordination. Journal of International Economics 32, 221-240.

Karnaukh, N., Ranaldo, A., Söderlind, P., 2015. Understanding FX Liquidity. Rev. Financ. Stud. 28, 3073–3108. doi:10.1093/rfs/hhv029

Kavli, H., Kotzé, K., 2014. Spillovers in exchange rates and the effects of global shocks on emerging market currencies. South African J. Econ. 82, 209–238. doi:10.1111/saje.12023

Koenker, R.W., Bassett, G., 1978. Regression Quantiles. Econometrica 46, 33–50. doi:10.2307/1913643

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. J. Econom. 74, 119–147. doi:10.1016/0304-4076(95)01753-4

Korinek, A., Mendoza, E.G., 2014. From Sudden Stops to Fisherian Deflation: Quantitative Theory and Policy. Annu. Rev. Econom. 6, 299–332. doi:10.1146/annurev-economics-080213-041005

Krugman, P.R., 2000. Currency crises. University of Chicago Press, Chicago.

Li, X.M., 2011. How do exchange rates co-move? A study on the currencies of five inflation-targeting countries. J. Bank. Financ. 35, 418–429. doi:10.1016/j.jbankfin.2010.08.019

Mancini, L., Ranaldo, A., Wrampelmeyer, J., 2013. Liquidity in the foreign exchange market: Measurement, commonality, and risk premiums. J. Finance 68, 1805–1841. doi:10.1111/jofi.12053

Melvin, M., Melvin, B.P., 2003. The Global Transmission of Volatility in the Foreign Exchange Market. Rev. Econ. Stat. 85, 670–679. doi:10.2307/3211705

Melvin, M., Taylor, M., 2009. The crisis in the foreign exchange market. Journal of International Money and Finance 28 (8), 1317-1330.

Parkinson, M., 1980. The Extreme Value Method for Estimating the Variance of the Rate of Return. J. Bus. 53, 61–65. doi:10.1086/296071

Patton, A.J., 2006. Modelling asymmetric exchange rate dependence. Int. Econ. Rev. (Philadelphia). 47, 527–556. doi:10.1111/j.1468-2354.2006.00387.x

Pesaran, M.H., Shin, Y., 1998. Generalized Impulse Response Analysis in Linear Multivariate Models. Econ. Lett. 58, 17–29. doi:10.1016/S0165-1765(97)00214-0

Reboredo, J.C., Rivera-Castro, M.A., Ugolini, A., 2016. Downside and upside risk spillovers between exchange rates and stock prices. J. Bank. Financ. 62, 76–96. doi:10.1016/j.jbankfin.2015.10.011

Rigobon, R., 2002. Contagion: How to Measure it?, in: Edwards, S., Frankel, J.A. (Eds.), Preventing Currency Crises in Emerging Markets. University of Chicago Press, Chicago, p. 720.

Wu, J.C., Xia, F.D., 2016. Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound. Journal of Money, Credit, and Banking 48(2-3), 253-291.

Appendix

Table A1. Summary statistics of the annualized volatility of the FX log-variations. The table shows summary statistics of FX volatility in annualized terms. The third and fourth moments of the series are presented for the logarithmic volatilities, which were used in the estimation of the spillover volatility indices. As expected, the series with the highest standard deviations and means are found in developing countries (i.e. South Africa, Brazil, and Colombia). In contrast, the lowest levels are found in developed countries (i.e. Europe and Japan).

	EUR	JPY	GBP	AUD	CAD	CHF	SEK	MXN	NZD	SGD
Mean	10.73	10.61	10.12	13.66	10.41	11.51	13.32	11.26	14.90	5.81
Median	9.57	9.26	8.83	11.64	9.26	10.30	11.61	9.34	13.11	5.07
Maximum	52.93	86.29	145.60	124.69	68.25	227.90	87.92	203.75	100.69	33.58
Minimum	0.00	0.42	0.00	1.53	1.27	0.00	1.82	0.00	2.19	0.33
Std. Dev.	5.58	6.33	6.06	8.66	5.65	7.11	7.25	9.05	8.12	3.10
Skewness	-0.13	-0.02	0.15	0.35	0.02	0.02	0.26	0.04	0.26	0.10
Kurtosis	3.50	3.89	3.86	3.91	3.31	4.02	3.17	4.43	3.59	3.96
	NOK	KRW	TRY	INR	BRL	ZAR	PLN	THB	COP	PHP
Mean	13.81	9.43	13.58	6.36	15.98	19.82	15.63	6.75	10.76	5.80
Median	12.24	7.39	11.20	5.46	13.62	17.03	13.41	5.08	8.19	5.32
Maximum	84.92	164.88	90.23	60.87	131.59	193.68	95.92	83.92	232.30	30.94
Minimum	2.06	0.00	0.00	0.00	0.00	1.48	0.45	0.00	0.00	0.00
Std. Dev.	7.31	9.03	9.14	5.28	10.47	11.28	9.27	6.04	9.97	3.65
Skewness	0.17	-0.35	-0.01	-0.77	-1.11	0.27	0.07	0.23	-0.89	-0.93
Kurtosis	3.23	4.49	4.63	3.76	7.24	3.89	3.70	4.09	5.09	4.36

Table A2. Estimated VaR summary statistics. The summary statistics were calculated from the VaR estimated after fitting a CAViaR model with asymmetric slopes. Commodity currencies, such as AUD, CAD, SEK, NZD, NOK, BRL, and ZAR, possess a higher risk than most of the other currencies. A second aspect that can be seen is that countries with capital control and with a history of foreign exchange interventions, such as INR, SGD and THB, have lower volatility.

	EUR	*JPY*	*GBP*	*AUD*	*CAD*	*CHF*	*SEK*	*MXN*	*NZD*	*SGD*
Mean	0.99	0.97	0.96	1.30	0.97	1.03	1.27	1.14	1.36	0.48
Median	0.96	0.93	0.90	1.19	0.89	0.98	1.19	1.03	1.27	0.45
Maximum	2.13	2.61	2.61	6.19	3.51	2.46	2.88	5.98	4.40	1.43
Minimum	0.47	0.50	0.40	0.66	0.41	0.47	0.77	0.44	0.69	0.22
Std. Dev.	0.29	0.26	0.34	0.55	0.36	0.28	0.36	0.54	0.44	0.15
Skewness	0.93	1.51	2.14	4.16	2.49	1.14	2.01	2.92	2.32	1.55
Kurtosis	4.40	7.43	9.43	28.88	13.47	5.55	7.59	17.90	11.86	7.19
	NOK	*KRW*	*TRY*	*INR*	*BRL*	*ZAR*	*PLN*	*THB*	*COP*	*PHP*
Mean	1.27	0.95	1.41	0.74	1.57	1.79	1.44	0.57	1.08	0.62
Median	1.20	0.80	1.26	0.67	1.40	1.66	1.28	0.49	0.91	0.59
Maximum	3.47	7.17	7.48	3.38	7.35	7.65	5.25	3.77	5.05	1.34
Minimum	0.65	0.32	0.58	0.08	0.55	0.93	0.52	0.17	0.30	0.30
Std. Dev.	0.35	0.68	0.63	0.40	0.74	0.59	0.63	0.35	0.57	0.16
Skewness	1.86	4.54	2.66	1.40	2.71	3.16	2.13	3.77	1.92	0.98
Kurtosis	8.91	30.91	14.98	6.77	15.56	21.59	9.39	22.55	9.25	4.20

Table A3. US determinants of cross-spillovers in depreciation quantiles. The table shows different specifications that seek to explain our quantile-based statistic of currency spillovers. We use as explanatory variables several combinations of the NBER recession indicator, the shadow rates of the effective federal funds proposed by Wu and Xia (2016), the TED spread, and the illiquidity index for currency markets proposed by Karnaukh et al. (2015). In each case we report the slope coefficients, standard errors in brackets, and the R-squared. The dataset spans the period January of 2004- September of 2016, with monthly frequency.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	65.67***	66.20***	66.09***	65.38***	65.52***
	(1.24)	(1.07)	(1.04)	(1.54)	(1.70)
NBER Recesions	3.87**				1.18
	(1.52)				(2.63)
Illiquidity Index		2.55**			2.62**
		(1.08)			(1.17)
FED Shadow Rate			-9.59***		-9.88***
			(3.07)		(3.72)
TED Spread				1.61	-3.18
				(1.41)	(2.85)
R-Squared	0.035	0.067	0.086	0.012	0.144

Note: (***) significance at 1% (**) Significance at 5% (*) Significance at 10%

Figure A1: Net volatility spillovers from *all* markets to market *i*. The figure shows net-volatility spillovers from the rest of the markets to each market. A positive value indicates that the market is a net-receiver, while a negative sign indicates that it is a net-transmitter of volatility on a certain date. The estimations were performed using rolling windows of 250 observations, a forecasting horizon of 10 days, and two lags in the case of volatility and one lag in the case of VaR-statistics. The VaR were constructed using an asymmetric CAViaR model.

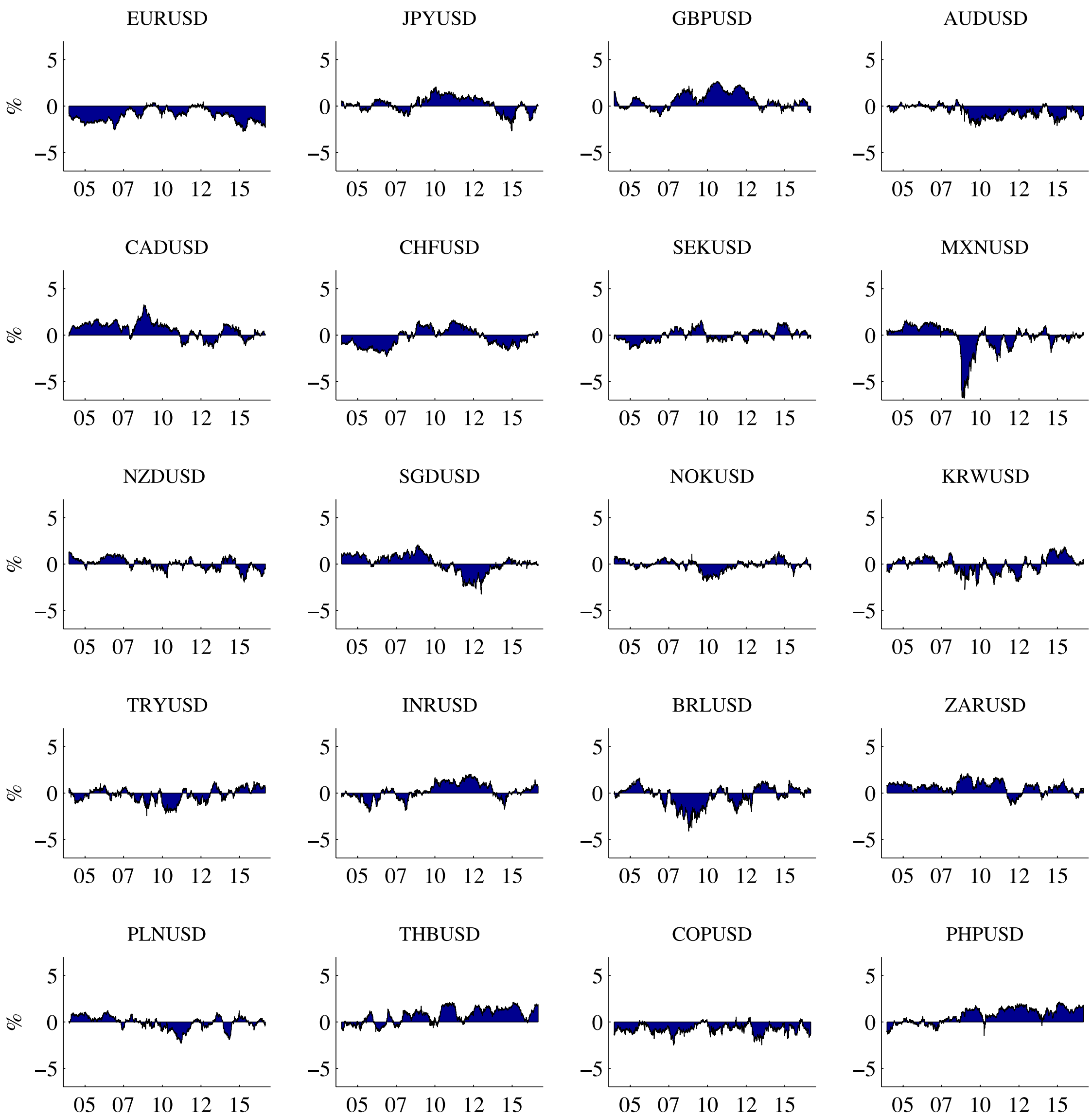


Figure A2: Net VaR spillovers from *all* markets to market *i*. The figure shows the net-value at risk spillovers from the rest of the markets to each market. A positive value indicates that the market is a net-receiver, while a negative sign indicates that it is a net-transmitter of volatility on a certain date. The estimations were performed using rolling windows of 250 observations, a forecasting horizon of 10 days, and two lags in the case of volatility and one lag in the case of VaR-statistics. The VaR were constructed using an asymmetric CAViaR model.