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RESEARCH ARTICLE

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Volatility impulse response analysis for DCC-GARCH models: The role of volatility transmission mechanisms

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Abstract

This study introduces volatility impulse response functions (VIRF) for dynamic conditional correlation–generalized autoregressive conditional heteroskedasticity (DCC-GARCH) models. In addition, the implications with respect to network analysis—using the connectedness approach of Diebold and Yılmaz (*Journal of Econometrics*, 2014, *182*(1), 119–134)—is discussed. The main advantages of this framework are (i) that the time-varying dynamics do not underlie a rolling-window approach and (ii) that it allows us to test whether the propagation mechanism is time varying or not. An empirical analysis on the volatility transmission mechanism across foreign exchange rate returns is illustrated. The results indicate that the Swiss franc and the euro are net transmitters of shocks, whereas the British pound and the Japanese yen are net volatility receivers of shocks. Finally, the findings suggest a high degree of comovement across European currencies, which has important portfolio and risk management implications.

KEYWORDS

volatility impulse response functions, volatility spillovers, variance decomposition, dynamic connectedness, exchange rates

1 | INTRODUCTION

Recent global economic developments have revived interest in propagation mechanisms that explain how economic shocks spread internationally. The transmission of shocks among economic entities is now becoming of major interest and concern, given that the effects of the aftermath of the Great Recession (2009) are still rippling through the world economy. Hence investigating the transmission mechanism is essential for policymakers to construct an early-warning system revealing the most important transmission channels.

That is why many researchers have developed methodologies in an attempt to capture this transmission process. A notable study, among many, is by (Diebold & Yilmaz, 2009, 2012, 2014), who introduce a dynamic connectedness procedure based on the notion of forecast error variance decomposition from vector autoregressions (VARs). This VAR-based network methodology has already attracted significant attention in the economic literature, and has been applied to the investigation of issues such as stock market interdependencies, business cycle synchronization, and volatility spillovers (see, among others,Antonakakis & Gabauer, 2017; Antonakakis, Gabauer, Gupta, & Plakandaras, 2018; Baruník, Kočenda, & Vácha, 2016; Bubák, Kočenda, & Žikeš, 2011; Corbet, Meegan, Larkin, Lucey, & Yarovaya, 2018; Demirer, Diebold, Liu, & Yilmaz, 2018; Gabauer & Gupta, 2018; Greenwood-Nimmo, Nguyen, & Shin, 2015; Klößner & Wagner, 2014; Wiesen, Beaumont, Norrbin, & Srivastava, 2018; Zhang & Broadstock, 2018).

The focus of this study is the introduction of an alternative framework that estimates the volatility transmission mechanisms which is becoming increasingly important in economics and finance (Antonakakis, Cunado, Filis, Gabauer, & De Gracia, 2018; Diebold & Yilmaz, 2009, 2012; Le Pen & Sévi, 2010; Nazlioglu, Erdem, & Soytas, 2013). So far the volatility transmission mechanism has been investigated as a two-step procedure, whereas in the first step a multivariate generalized autoregressive heteroskedasticity (GARCH) procedure is utilized to receive time-varying volatilities which are used in the second step as fundamentals of a rolling-window VAR estimation procedure. Among others, this procedure is employed by (Beirne, Caporale, Schulze-Ghattas, and Spagnolo; 2013, Hoesli and Reka; 2013), and Antonakakis (2012).

Besides the fact that the second step could be based on inaccurate first-step results, the rolling-window approach has two main disadvantages: (i) the window size is in most cases chosen arbitrarily; and (ii) the rolling-window analysis leads to a loss of observations.

Thus this paper introduces volatility impulse response functions (VIRFs) and proposes an alternative to the volatility connectedness approach of (Diebold & Yilmaz, 2014) without facing the previously mentioned disadvantages. Up until now, VIRFs (Hafner & Herwartz, 2006; Lin, 1997) have been developed for VEC-GARCH (vector error correction; (Bollerslev, Engle, & Wooldridge, 1988)), BEKK-GARCH (named after Baba, Engle, Kraft, and Kroner; see (Engle & Kroner, 1995)), and CCC-GARCH (constant conditional correlation; (Bollerslev, 1990)) models; however, this is not the case for the DCC-GARCH framework (Engle, 2002). Developing VIRFs for DCC-GARCH models is of major interest since it is one of the most often used multivariate GARCH models; this is due to the fact that it is not as severely affected by the curse of dimensionality as its alternatives (Bauwens, Laurent, & Rombouts, 2006; Silvennoinen & Teräsvirta, 2009).

Hence this paper is the first to provide VIRFs for DCC-GARCH and additionally proposes an alternative to the volatility transmission mechanism estimated via the dynamic connectedness approach of Diebold and Yilmaz (2014) without using a rolling-window framework. In addition, the DCC test introduced by Engle and Sheppard (2001) is employed, which provides information on whether spillovers are varying over time. Findings suggest that the spillovers are indeed varying over time and that the Swiss franc is the main dominant net transmitter, followed by the euro, whereas the main transmitters are the British pound, followed by the Japanese yen.

The remainder of this study is organized as follows. Section 2 describes the data and the proposed methodology. Section 3 illustrates the empirical results of the foreign exchange rate transmission mechanism, and finally, Section 4 concludes this study.

2 | DATA AND METHODOLOGY

The employed data set is obtained from the Bank of England online database[1] and consists of daily spot exchange rates of the euro (EUR), Swiss franc (CHF), British pound (GBP), and Japanese yen (JPY), all against the US dollar (USD), ranging over the period from January 2, 2002, to September 21, 2018. Since the exchange rates are nonstationary according to the ERS unit root test (Stock, Elliott, & Rothenberg, 1996), their returns are analyzed by taking the first log-differences: $y_{it} = \log(x_{it}) - \log(x_{it-1})$.

The summary statistics of the returns are depicted in Table 1 and show that all series are significantly skewed, exhibit excess kurtosis, and are not normally distributed at at least the 5% significance level. Furthermore, all series are stationary and exhibit ARCH errors at the 1% significance level, which indicates that estimating a multivariate GARCH procedure seems to be appropriate.

2.1 | DCC-GARCH

To examine the time-varying conditional volatility, the two-step DCC-GARCH model àla Engle (2002) is employed. The DCC-GARCH(1,1) model can be written as follows:

$$\boldsymbol{y}_t = \boldsymbol{\mu}_t + \epsilon_t \quad \epsilon_t|\boldsymbol{F}_{t-1} \sim N(\boldsymbol{0}, \boldsymbol{H}_t), \tag{1}$$

$$\epsilon = \boldsymbol{H}_t^{1/2}\boldsymbol{u}_t \quad \boldsymbol{u}_t \sim N(\boldsymbol{0}, \boldsymbol{I}), \tag{2}$$

$$\boldsymbol{H}_t = \boldsymbol{D}_t\boldsymbol{R}_t\boldsymbol{D}_t, \tag{3}$$

where $\boldsymbol{F}_{t-1}$ stands for all information available up to $t-1$. $\boldsymbol{y}_t$, $\boldsymbol{\mu}_t$, ϵ_t, and $\boldsymbol{u}_t$ are $N{\times}1$-dimensional vectors representing the analyzed time series, conditional mean, error term, and standardized error term, respectively. Furthermore, $\boldsymbol{R}_t$, $\boldsymbol{H}_t$, and $\boldsymbol{D}_t = \text{diag}(h_{11t}^{1/2}, \dots, h_{NNt}^{1/2})$ are $N \times N$-dimensional matrices, illustrating the dynamic conditional correlations, time-varying conditional variance–covariance matrices, and the time-varying conditional variances.

At the first stage, $\boldsymbol{D}_t$ is created by estimating a Bollerslev (1986) GARCH model for each series. Based on the study of Hansen and Lunde (2005), one shock and one persistency parameter are assumed:

$$h_{ii,t} = \omega + \alpha\epsilon_{i,t-1}^2 + \beta h_{ii,t-1}. \tag{4}$$

[1]The data that support the findings of this study are available from the corresponding author upon reasonable request.

At the second stage, the dynamic conditional correlations are computed as follows:

$$\boldsymbol{R}_t = \mathrm{diag}\left(q_{iit}^{-1/2}, \ldots, q_{NNt}^{-1/2}\right) \boldsymbol{Q}_t \, \mathrm{diag}\left(q_{iit}^{-1/2}, \ldots, q_{NNt}^{-1/2}\right), \quad (5)$$

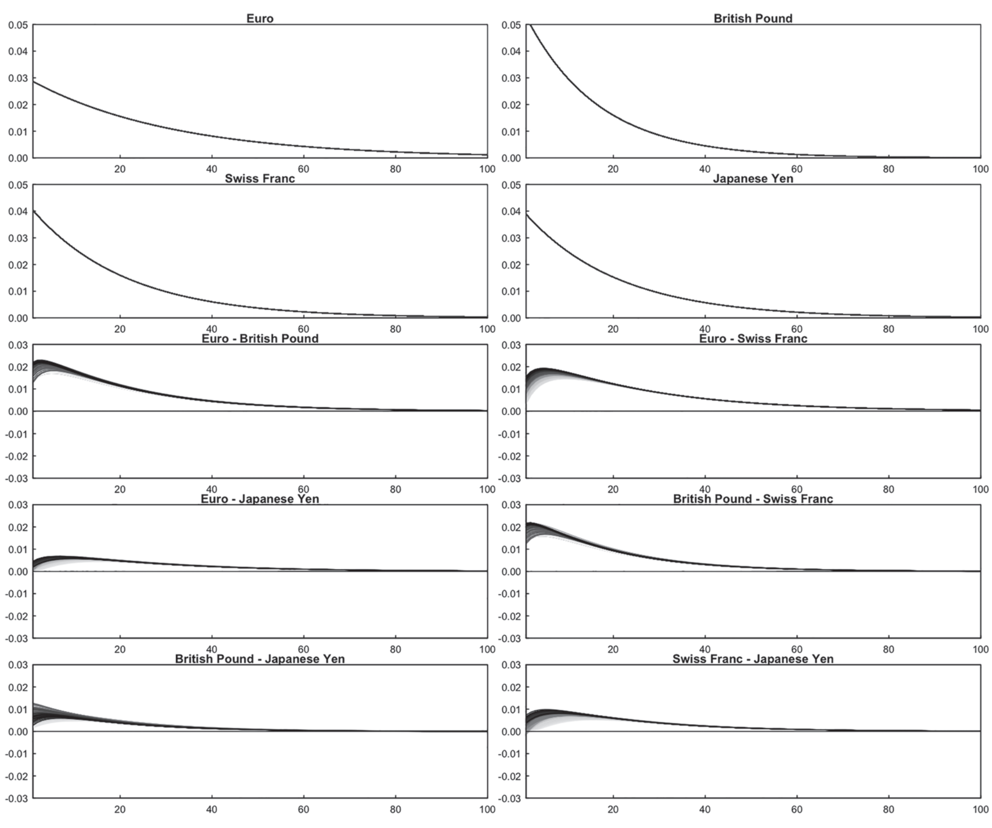
$$\boldsymbol{Q}_t = (1 - a - b)\bar{\boldsymbol{Q}} + a\boldsymbol{u}_{t-1}\boldsymbol{u}'_{t-1} + b\boldsymbol{Q}_{t-1}, \quad (6)$$

where $\boldsymbol{Q}_t$, and $\bar{\boldsymbol{Q}}$ are $N \times N$-dimensional positive-definite matrices which represent the conditional and uncondi-

TABLE 1 Summary statistics

	Euro	British pound	Swiss franc	Japanese yen
Mean	0.006	-0.003	0.013	0.004
Variance	0.37	0.369	0.478	0.408
Skewness	0.084**	-0.832***	1.239***	0.314***
	(0.024)	(0.000)	(0.000)	(0.000)
Kurtosis	2.549***	12.133***	37.707***	4.312***
	(0.000)	(0.000)	(0.000)	(0.000)
JB	1,163.426***	26,739.577***	254,585.699***	3,385.860***
	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-9.563***	-18.094***	-10.059***	-13.378***
	(0.000)	(0.000)	(0.000)	(0.000)
$Q^2(20)$	567.714***	441.749***	89.666***	309.857***
	(0.000)	(0.000)	(0.000)	(0.000)
LiMak(20)	300.429***	201.264***	17.023*	177.631***
	(0.000)	(0.000)	(0.057)	(0.000)
		Unconditional correlations		
Euro	1.000	0.645	0.764	0.312
British pound	0.645	1.000	0.491	0.133
Swiss franc	0.764	0.491	1.000	0.419
Japanese yen	0.312	0.133	0.419	1.000

Notes. Asterisks denote significance at ***1%, **5%, and *10% significance level; Skewness: D'Agostino (1970) test; kurtosis: Anscombe and Glynn (1983) test; JB: Jarque and Bera (1980) normality test; ERS: Stock et al. (1996) unit-root test; $Q^2(20)$ and LiMak(20): Fisher and Gallagher (2012) weighted portmanteau test.



Notes: All exchange rates are against the USD.

FIGURE 1 Volatility impulse response functions. All exchange rates are against the USD tional standardized residuals' variance–covariance matrices, respectively. a (α) and b (β) are nonnegative shock and persistency parameters, satisfying $a + b < 1$ ($\alpha + \beta \leq 1$). As long as $a + b < 1$ is fulfilled, $\boldsymbol{Q}_t$ and hence $\boldsymbol{R}_t$ are varying over time, otherwise this model would converge to the CCC-GARCH model, where $\boldsymbol{R}_t$ is constant over time.

2.2 | Volatility impulse response function

It should be noted that the connectedness approach introduced by (Diebold & Yilmaz, 2012, 2014) rests on the generalized impulse response functions (GIRFs) introduced by Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998). GIRFs have the advantage of being independent of the variable ordering and can be interpreted as the J-step-ahead impact of a shock in variable i on variable j: $\text{GIRF}(J, \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) = E(\boldsymbol{y}_{t+J}|\epsilon_{j,t} = \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) - E(\boldsymbol{y}_{t+J}|\epsilon_{j,t} = \boldsymbol{0}, \boldsymbol{F}_{t-1})$.

In the same spirit, the VIRF represents the impact of a shock in variable i on variable j's conditional volatilities, which can be written as

$$\begin{aligned}\boldsymbol{\Psi}^{g} = \text{VIRF}(J, \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) &= E(\boldsymbol{H}_{t+J}|\epsilon_{j,t} = \boldsymbol{\delta}_{j,t}, \boldsymbol{F}_{t-1}) \\ &- E(\boldsymbol{H}_{t+J}|\epsilon_{j,t} = \boldsymbol{0}, \boldsymbol{F}_{t-1}),\end{aligned} \tag{7}$$

where $\boldsymbol{\delta}_{j,t}$ is a selection vector with a one at the jth position and zero otherwise.

Forecasting the conditional variance–covariances using the DCC-GARCH model (Engle & Sheppard, 2001) lies at the heart of the VIRF and can be accomplished iteratively in three steps. First, the univariate GARCH(1, 1) will forecast the conditional volatilities ($\boldsymbol{D}_{t+h}|\boldsymbol{F}_t$) by

$$E(h_{ii,t+1}|\boldsymbol{F}_t) = \omega + \alpha\delta_{1,t}^2 + \beta h_{ii,t} h = 1, \tag{8}$$

$$\begin{aligned}E(h_{ii,t+h}|\boldsymbol{F}_t) = &\sum_{i=0}^{h-1}\omega(\alpha + \beta)^i \\ &+ (\alpha + \beta)^{h-1}E(h_{ii,t+h-1}|\boldsymbol{F}_t) h > 1,\end{aligned} \tag{9}$$

whereas, in a second step, $E(\boldsymbol{Q}_{t+h}|\boldsymbol{F}_t)$ is predicted according to

$$E(\boldsymbol{Q}_{t+1}|\boldsymbol{F}_t) = (1 - a - b)\bar{\boldsymbol{Q}} + a\boldsymbol{u}_t\boldsymbol{u}_t' + b\boldsymbol{Q}_t h = 1, \tag{10}$$

$$\begin{aligned}E(\boldsymbol{Q}_{t+h}|\boldsymbol{F}_t) = (1 - a - b)\bar{\boldsymbol{Q}} &+ aE(\boldsymbol{u}_{t+h-1}\boldsymbol{u}_{t+h-1}'|\boldsymbol{F}_t) \\ &+ bE(\boldsymbol{Q}_{t+h-1}|\boldsymbol{F}_t) h > 1,\end{aligned} \tag{11}$$

where $E(\boldsymbol{u}_{t+h-1}\boldsymbol{u}_{t+h-1}'|\boldsymbol{F}_t) \approx E(\boldsymbol{Q}_{t+h-1}|\boldsymbol{F}_t)$ (Engle & Sheppard, 2001), which helps in forecasting the dynamic conditional correlations and finally the conditional variance–covariances:

$$\begin{aligned}E(\boldsymbol{R}_{t+h}|\boldsymbol{F}_t) \approx \text{diag}&\left[E(q_{iit+h}^{-1/2}|\boldsymbol{F}_t), \dots, E(q_{NNt+h}^{-1/2}|\boldsymbol{F}_t)\right] \\ E(\boldsymbol{Q}_{t+h})\text{diag}&\left[E\left(q_{iit+h}^{-1/2}|\boldsymbol{F}_t\right), \dots, E\left(q_{NNt+h}^{-1/2}|\boldsymbol{F}_t\right)\right],\end{aligned} \tag{12}$$

$$E(\boldsymbol{H}_{t+h}|\boldsymbol{F}_t) \approx E(\boldsymbol{D}_{t+h}|\boldsymbol{F}_t)E(\boldsymbol{R}_{t+h}|\boldsymbol{F}_t)E(\boldsymbol{D}_{t+h}|\boldsymbol{F}_t). \tag{13}$$

2.3 | Dynamic connectedness approach

Based on the VIRF, the generalized forecast error variance decomposition (GFEVD) is computed, which can be interpreted as the variance share one variable explains on others. These variance shares are normalized, so that each row sums up to one, meaning that all variables together explain 100% of variable i's forecast error variance. This is calculated as follows:

$$\tilde{\phi}_{ij,t}^{g}(J) = \frac{\sum_{t=1}^{J-1}\Psi_{ij,t}^{2,g}}{\sum_{j=1}^{N}\sum_{t=1}^{J-1}\Psi_{ij,t}^{2,g}}, \tag{14}$$

where $\sum_{j=1}^{N}\tilde{\phi}_{ij,t}^{g}(J) = 1$ and $\sum_{i,j=1}^{N}\tilde{\phi}_{ij,t}^{g}(J) = N$. The numerator represents the cumulative effect of the ith shock, while the denominator represents the aggregate cumulative effect of all the shocks. Using the GFEVD, the total connectedness index (TCI) can be constructed by

$$C_t^{g}(J) = \frac{\sum_{i,j=1, i\neq j}^{N}\tilde{\phi}_{ij,t}^{g}(J)}{N}. \tag{15}$$

Subsequently, the spillovers variable i transmits to variables j, which are called *total directional connectedness TO*

TABLE 2 Dynamic connectedness table

	Euro	British pound	Swiss franc	Japanese yen	FROM
Euro	49.2	13.8	32.2	4.9	50.8
British pound	26.6	49.4	20.8	3.2	50.6
Swiss franc	30.0	10.0	52.3	7.7	47.7
Japanese yen	8.4	2.8	14.1	74.7	25.3
Contribution TO others	65.0	26.6	67.1	15.8	174.4
NET directional connectedness	14.1	-24.0	19.3	-9.4	TCI
NPSO transmitter	2.0	0.0	3.0	1.0	58.2

Note. Values reported are variance decompositions based on 100-day-ahead forecasts.

others and are computed by

$$C^{g}_{i\to j,t}(J)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\phi}^{g}_{ji,t}(J)}{\sum_{j=1}^{N}\tilde{\phi}^{g}_{ji,t}(J)}. \tag{16}$$

In a next step, the spillovers variable i receives from variables j, which are called *total directional connectedness FROM others*, and are calculated as follows:

$$C^{g}_{i\leftarrow j,t}(J)=\frac{\sum_{j=1,i\neq j}^{N}\tilde{\phi}^{g}_{ij,t}(J)}{\sum_{i=1}^{N}\tilde{\phi}^{g}_{ij,t}(J)}. \tag{17}$$

Subtracting the two aforementioned measures from each other leads to the *net total directional connectedness*, which can be interpreted as the influence variable i has on the analyzed network:

$$C^{g}_{i,t}=C^{g}_{i\to j,t}(J)-C^{g}_{i\leftarrow j,t}(J). \tag{18}$$

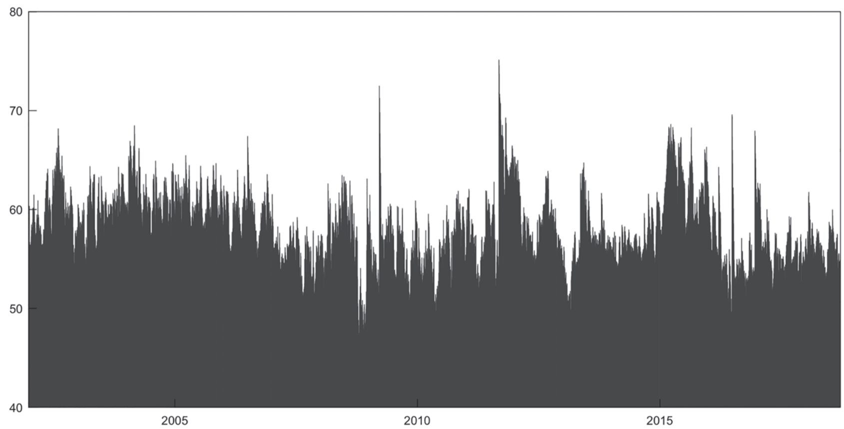
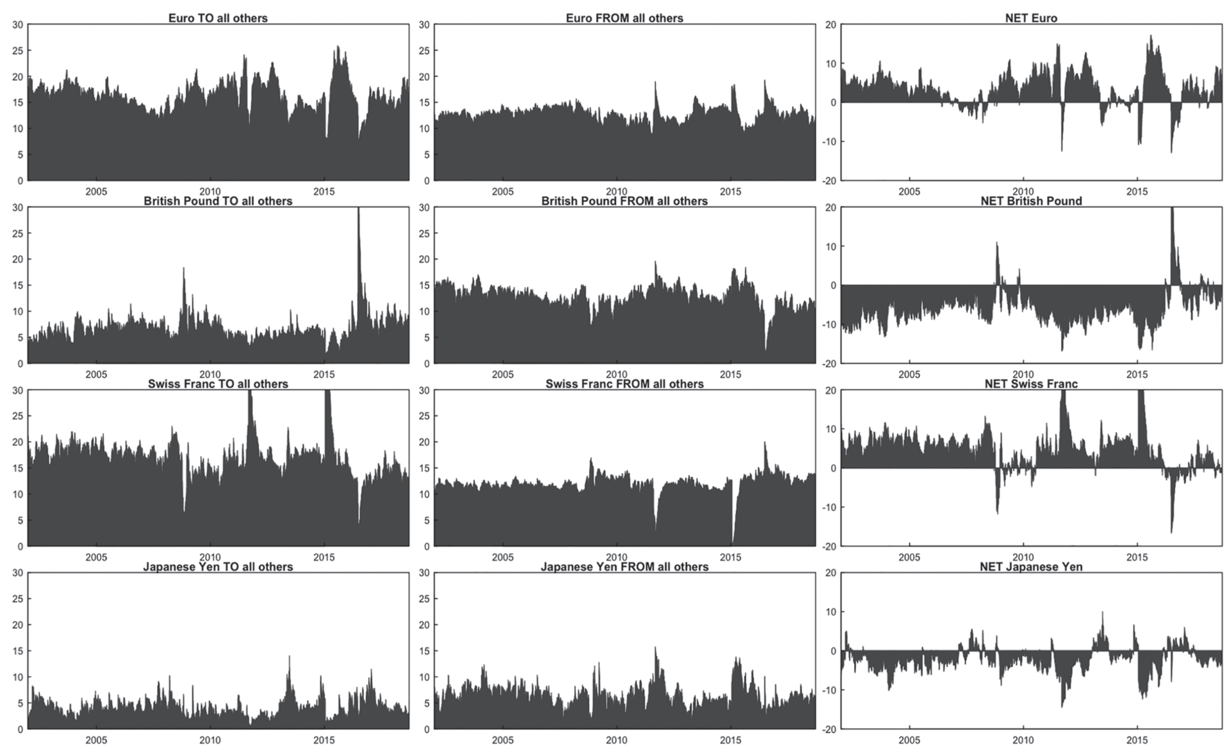


FIGURE 2 Dynamic total connectedness



Notes: All exchange rates are against the USD.

FIGURE 3 Net total directional connectedness. All exchange rates are against the USD

If the net total directional connectedness of variable i is positive (negative), it means that variable i is a net transmitter (receiver) of shocks or that variable i is driving (driven by) the network.

Finally, the net pairwise directional connectedness (NPDC) between variable i and variable j is computed as follows:

$$\mathrm{NPDC}_{ij}(J) = \tilde{\phi}^{g}_{ji,t}(J) - \tilde{\phi}^{g}_{ij,t}(J), \tag{19}$$

where a positive (negative) NPDC_{ij} indicates that variable i dominates (is dominated by) variable j.

3 | EMPIRICAL RESULTS

3.1 | Volatility impulse responses

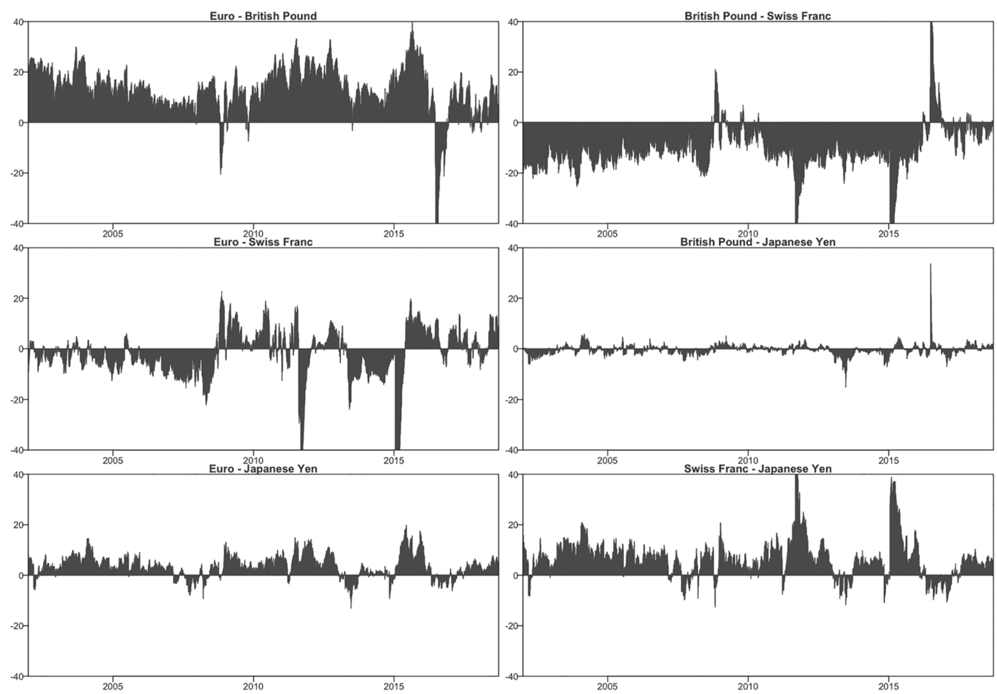
The results, which are illustrated in Figure 1, show that the volatility spillovers are highly persistent. Furthermore, the cross-volatility spillovers represent that an increase in the volatility of one series increases the volatility of the others. The effects only differ by their magnitude and persistency. In addition, it can be observed that the persistency across European currencies is higher than with respect to the JPY. This could be an indication of regional currency contagion supporting the findings of Glick and Rose (1999). In addition, this result provides essential insights in terms of diversification and hence for portfolio and risk management. Finally, the DCC test (Engle & Sheppard, 2001) (p-value of $7.436e-13$) provides strong evidence that spillovers are changing over time.

3.2 | Dynamic connectedness table

Table 2 illustrates the averaged dynamic connectedness measures. The static TCI is equal to 58.2%, indicating that the foreign exchange rate market is highly interconnected. Furthermore, the findings suggest that the CHF is the main net transmitter since it is the net transmitter to all three other currencies followed by the EUR. On the other hand, the main net receiver is the GBP, which receives from all others, followed by the JPY, which slightly dominates the GBP but is dominated by all others as well.

3.2.1 | Dynamic total connectedness

Figure 2 depicts the dynamic TCI spanning approximately between 50% and 75%. This practically implies that connectedness across foreign exhange rates is strong and time varying, a fact which is typically masked by the nature of the static TCI. To be more explicit, two spikes can be observed in Figure 3, whereupon the first can be associated with the Great Recession (2009) and the second with the second Greek bailout aid (2012). The persistency of peaks illustrates periods of high interconnectedness such as during the subprime market crisis (2007–2009), the PIIGS (Portugal, Ireland, Italy, Greece, and Spain) crisis (2011–2012), and finally in 2015 when Greece asked for another bailout aid. At the end of the period a stable and low level of interconnectedness is reached, indicating a decreased risk level in the foreign exchange rate market.



Notes: All exchange rates are against the USD.

FIGURE 4 Net pairwise directional connectedness. All exchange rates are against the USD

3.2.2 | Net directional connectedness measures

The dynamic net total directional connectedness measures are illustrated in Figure 3. The findings suggest that the lowest influence of the EUR is observed in 2007 during the US subprime market crisis. The negative spikes can be associated with the first, second, and third Greek bailout aid (2010, 2012, 2015). In the case of the GBP, the two positive peaks can be associated with the important role the UK financial market had during the Great Recession and the Brexit news, which had a strong influence on the GBP. Furthermore, the CHF had been a net transmitter until the Great Recession, when it temporarily became a net receiver of shocks. The first positive spike can be observed when the CHF starts pegging its value to the EUR in 2011, whereas the second positive peak illustrates the CHF unpegging from the EUR. Moreover, the largest negative value, which occurs at the beginning of 2016, can be explained by the 40% increase in the CHF with respect to the EUR.

Figure 4 supports all previous findings—in particular, that the GBP dominates the EUR and the CHF in 2009 and after the Brexit referendum. The CHF reaches its highest value against all others when it pegged and later unpegged its value to the EUR. Throughout the analyzed period, the CHF and the EUR are nearly constantly dominating the JPY. The bilateral relationship between the GBP and the JPY is rather weak and the only peak can be explained by the outcome of the Brexit referendum in mid-2015.

4 | CONCLUDING REMARKS

This study develops VIRFs for DCC-GARCH models and proposes an alternative to the rolling-window analysis of the dynamic connectedness framework of (Diebold & Yilmaz, 2009, 2012, 2014). The main advantage of the outlined procedure is that no arbitrarily chosen window size is necessary, which in turn means that no observations are lost and that it can be tested whether spillovers are time varying or not. Hence this procedure improves the current volatility spillover literature in multiple ways by providing more detailed insights into network-related propagation mechanism dynamics. Finally, an empirical analysis regarding the volatility spillovers in the foreign exchange rate market is discussed. The results indicate that spillovers are indeed time varying and that the CHF is the main net transmitter of shocks, followed by the EUR, whereas the main net receivers are the GBP followed by the JPY. The highest intercorrelations are observed across European currencies, indicating the presence of regional currency contagion, which has essential portfolio and risk management implications.

Further research avenues are the monitoring and forecasting of asset volatility comovements and spillovers, which are highly relevant for portfolio and risk management. Those features are playing a central role when it comes to the trading, pricing, and evaluation of options, futures, and other derivatives. Furthermore, it could also be worthwhile to investigate how the degree of volatility interconnectedness—which is often used as a proxy for market uncertainty and investors' sentiment—influences how investors distribute their budget across risky assets, which in turn opens further research avenues in the field of money and liquidity management. Finally, this framework could also be used to examine the irregularity of persistent and volatile behavior of time-varying portfolio weights (Kroner & Sultan, 1993) and hedge ratios (Kroner & Ng, 1998).

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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