

Heterogeneous Behavior and Volatility Transmission in the Forex Market using High- Frequency Data

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Abstract

This paper examines the dynamics of volatility transmission in the forex market using high-frequency data for five exchange rates (EUR/USD, EUR/JPY, EUR/CHF, EUR/GBP and EUR/AUD) from January 2004 to October 2014. We apply a multivariate HAR model in which the daily realized volatility of a given exchange rate depends on both its own lags and the lagged realized volatilities of the other exchange rates. Furthermore, this model is able to identify short-term, medium-term, and long-term transmission effects. We also find evidence of statistically significant volatility transmission between exchange rates in the forex market, especially during periods marked by market uncertainty.

JEL classification numbers: C5, F31, G15.

Keywords: Foreign exchange markets, Realized volatility, High-frequency data, Volatility transmission, HAR model, DCC-GARCH.

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1. Introduction

The progressive integration of the world's financial markets has given rise to many endeavors focused on volatility transmission between financial markets, especially the foreign exchange (Forex) market. This is relatively important for hedging strategies, risk management, and the regulation of financial markets. Although considerable attention has been paid to studying volatility transmission in equity markets (Hamao et al., 1990; Malik and Ewing, 2009; Corradi et al., 2012; Gardebroek and Hernandez, 2013; and Tian and Hamori, 2016), similar studies for the forex market are not so commonplace. In addition, studies into volatility transmission in financial markets are mostly based on low-frequency data. According to Soriano and Climent (2006), most studies in this field apply multivariate models that are based on latent volatility measures. In addition, the generalized autoregressive conditional heteroskedasticity (GARCH) and the autoregressive conditional heteroskedasticity (ARCH) models, for example, are unable to capture some of the statistical properties of financial returns, such as the persistence of shocks and the presence of long memory. What is more, Davidson and Mackinnon (2004) assert that GARCH models are unable to take into account some stylized facts in a financial time series.

The contribution of this study is threefold. First, it is the first study to employ the multivariate extension of the heterogeneous autoregressive (HAR) model of Corsi (2009) for realized volatility in order to explore volatility transmission in the forex market. Corsi (2009) introduced the HAR model in order to estimate realized volatility. This model can capture the persistence of realized volatility and give a clear economic interpretation for results. In this study, the researcher associates the realized volatility with the heterogeneity of investors in the market in order to capture the long-term dependency properties of the daily realized volatility and how it relates to the weekly and monthly realized volatility. Different time horizons are considered as a source of heterogeneity, with three types of investors with different time horizons according to their frequency of activity (Dacorogna et al., 1993; Muller et al., 1997) being distinguished. The first group includes operators who act on an intraday basis, such as dealers and speculators. The second group comprises investors who make their decisions on a weekly basis, such as portfolio managers. The third group involves central banks, funds, and commercial organizations that operate on a monthly basis. Each of these investor groups creates varying volatilities in the forex market. The HAR model provides a simple and powerful regression that divides transmission effects for daily, weekly and monthly horizons. We build our analysis on the multivariate version developed by Bubák et al. (2011).

The second contribution is the adaptation of the multivariate HAR model to the series of realized volatility of the exchange rates under consideration (Andersen et al., 2007; Bubák et al., 2011; and Souček and Todorova, 2014). We therefore consider the volatility as an observable variable based on high-frequency (intraday) return measures, specifically data sampled at a periods shorter than a trading day (Goodhart and O'Hara, 1997; Gençay et al., 2001; and Engle and Gallo, 2006).

Wongswan (2006) suggests that high-frequency data are more efficient than their low-frequency counterparts (sampling periods of a day or longer) in capturing the presence of volatility transmission in the forex market. Thus, a notable benefit to using realized volatility instead of latent volatility, as opposed to in traditional methods, is an improvement in the volatility estimation and subsequently the implication of volatility transmission. Other benefits have been discussed in several studies (Andersen, Bollerslev, Diebold, and Ebens, 2001; Andersen et al., 2000; Andersen, Bollerslev, Diebold, and Labys, 2001; Andersen et al., 2003; Andersen et al., 1999). For this reason, we use high-frequency data in this study (samples every minute) in order to construct the daily realized volatility (which is known as the historic volatility).

For the third contribution of this study, we examine the volatility transmission in the forex market for five exchange rates (EUR/USD, EUR/JPY, EUR/CHF, EUR/GBP, and EUR/AUD) for the period from January 2004 to October 2014. The financial turbulence from 2008 to 2011 was mostly due to the subprime financial crisis and the subsequent sovereign debt crisis. These developments led to a renewed interest in studying the volatility transmission processes in international financial markets. How significant events influence the markets motivates us to learn about the dynamics of volatility transmission between currencies, considering the periods before, during, and after crises separately. The empirical results reveal the existence of volatility transmissions in the forex market. We find that each exchange rate is characterized by a different volatility transmission pattern before, during, and after a crisis period.

This paper is organized as follows: Section 2 provides a review of literature relevant to volatility transmission in the forex market and the HAR model. Sections 3 and 4, meanwhile, present the data and the methodology. Section 5 then discusses the empirical results, while Section 6 supplies this study's conclusion.

2. Literature review

Several researchers have studied the dynamics of exchange rate volatility, but few have examined volatility transmission in the forex market.

In most cases, studies that focus on volatility transmission in the forex market apply a GARCH class model (Bollerslev, 1990; Kearney and Patton, 2000; Speight and McMillan, 2001; Black and McMillan, 2004; and Calvet et al., 2006; McMillan and Speight, 2010; and Khalifa et al., 2016). Bollerslev (1990), meanwhile, applies a multivariate GARCH model to examine the volatility transmission of five European weekly exchange rates against the USD during and after the creation of the European Monetary System. The results show a significant volatility transmission between the exchange rates involved. In other work, Kearney and Patton (2000) apply a multivariate BEKK model (Baba, Engle, Kraft and Kroner developed by Engle and Kroner (1995) in order to examine the DEM/USD, FRF/USD, ITL/USD and GBP/USD exchange rates between April 1979 and March 1997. They reveal that the DEM/USD rate dominates other exchange rates and is barely affected by

external shocks, but it transmits more volatility than other exchange rates. Furthermore, they find evidence to show that less volatile weekly data shows a significantly smaller tendency to transmit volatility than more volatile daily data. In their study, Laborde and Rey (2001) apply a vector autoregressive (VAR) model in order to analyze the causal relationship between EUR/USD volatility and asset prices in US and French market volatilities by using daily and weekly data. The results reveal that US stock prices Granger-cause French stock prices, while changes in French and American stock prices significantly influence the EUR/USD rate. In addition, they show that the volatilities of stock markets are affected by EUR/USD volatility. What is more, with weekly data, they find that EUR/USD volatility Granger-causes stock prices. Nikkinen et al. (2006) also use a VAR model to study volatility transmission between the GBP, EUR, and CHF currencies from January 2001 to September 2003, with the greatest correlation seeming to exist between EUR and CHF. In addition, the euro appears to be the most dominant of these currencies. Pérez-Rodríguez et al. (2006), meanwhile, employ the dynamic conditional correlation (DCC-) GARCH model of Engle (2002) to prove the presence of volatility transmission between the EUR/USD, GBP/USD, and JPY/USD rates during the period after the introduction of the euro. Furthermore, they indicate the importance of short-term dynamics to the forex market. Inagaki (2007), meanwhile, applies a residual cross-correlation approach to examine volatility transmission between the EUR/USD and the GBP/USD exchange rates. The researchers observe how the EUR/USD rate Granger-causes the GBP/USD rate in variance but that the GBP/USD rate does not Granger-cause the EUR/USD rate in variance. This result supports a unidirectional volatility transmission from the EUR/USD rate to the GBP/USD rate, suggesting that euro traders succeed in efficiently processing information derived from the British pound. Indeed, McMillan and Speight (2010) analyze the volatility transmission between three exchange rates—namely EUR/USD, EUR/JPY, and EUR/GBP—and apply the realized variance method to avoid the weakness of GARCH models. The estimation results of the VAR model suggest that EUR/USD volatility dominates the other two rates in terms of return and volatility spillovers. More recently, Khalifa et al. (2016) show the existence of volatility transmission across currencies and commodities using the Multi-Chain Markov Switching model. Tian and Hamori (2016), however, present evidence from the United States for the volatility transmission mechanism in the foreign exchange, equity, bond, and commodity markets using a time-varying structural vector autoregression model with stochastic volatility. Furthermore, Tule et al. (2017) indicate the presence of volatility transmission between the stock market and the forex market using a multivariate GARCH model.

Within the context of realized volatility, Baillie and Bollerslev (1991) look for the presence of volatility transmission in the spot series for four foreign exchange rates (GBP/USD, JPY/USD, DEM/USD, and CHF/USD) based on hourly data for a six-month period in 1986. They use the seasonal GARCH model to illustrate the time-dependent volatility between currencies. However, they fail to find any evidence

for the presence of volatility transmission between currencies or across markets. Melvin and Melvin (2003), in contrast, provide evidence of a statistically significant transmission between the DEM/USD and the JPY/USD integrated volatilities using high-frequency data for the forex market. Similarly, Cai et al. (2008) use high-frequency data to show the presence of volatility transmission between the EUR/USD and USD/JPY rates across five trading regions (the Asia Pacific region, the Asia–Europe overlap, Europe, the Europe–America overlaps, and America). Clements et al. (2015), meanwhile, examine the transmission of volatility in the global foreign exchange, equity, and bond markets. By using a multivariate GARCH framework that considers realized volatility measures, they find significant volatility transmission between Japan, Europe and the United States. In their study, Kenourgios et al. (2015) investigate intraday exchange rate volatility transmissions across quantitative easing announcements. They indicate the existence of an increased volatility transmission from GBP to EUR around announcements from the Bank of England.

Recently, numerous studies into volatility transmission have adopted the HAR model of Corsi (2009) for realized volatility. The success of the HAR model has also been shown in other markets (Chiriac and Voev, 2011; Corsi et al., 2012). Indeed, Souček and Todorova (2013) study the realized volatility transmission between crude oil and equity futures markets using a multivariate HAR approach and find significant spillovers between equity and oil futures volatility, especially during crisis period. In a recent study, Degiannakis et Filis (2017) concentrate on realized volatilities derived from the intra-day prices of the Brent crude oil and four different asset classes (Stocks, Forex, Commodities and Macro) using a HAR framework.

However Todorova et al. (2014) study the metal futures market; they provide evidence for significant volatility transmission in the long term using a multivariate HAR model for realized volatility established from intraday futures data. Similarly, Lyócsa et al. (2017) explore multiple extensions of the HAR model using intraday data in order to study the realized volatility transmission in the metal futures market too.

Andersen et al. (2007) suggest that this model allows the adjustment of volatility over different time horizons and can capture the slow decay of the autocorrelations in the volatility series. Thus, Bubák et al. (2011) are the first to employ the HAR model on its multivariate framework. They analyze the transmission of realized volatility between the EUR/USD rate and the central European currencies during 2003–2009. They show evidence of volatility transmission between the central European currencies, but no significant transmission is observed from the EUR/USD rate to the central European currencies. In a recent study, Souček et Todorova (2014) employ a HAR model considering continuous and jump volatility components applied to financial, commodity and forex intraday futures data. The authors find a significant volatility transmission among these markets.

3. Methodology

The daily realized volatility (RV) is constructed with high-frequency data. This method was introduced by French et al. (1987), who estimated monthly-realized volatility through the daily returns. First, let r_t be the logarithmic return process. The realized variance over an interval $[t - h, t]$ is then defined as:

$$RVar_{t,h} = \sum_{i=1}^n r_{t-h+\frac{i}{n}}^2, \quad (1)$$

With, n being the number of observations over the interval $[t - h, t]$.

Thus, the realized volatility, as the square root of the variance, is calculated as:

$$RV_{t,h} = \sqrt{RVar_{t,h}}, \quad (2)$$

The autoregressive heterogeneous model (HAR) proposed by Corsi (2009) is defined as:

$$RV_{td}^{(d)} = \beta_0 + \beta^{(d)}RV_{t-1}^{(d)} + \beta^{(w)}RV_{t-1}^{(w)} + \beta^{(m)}RV_{t-1}^{(m)} + \epsilon_{td}^{(d)}, \quad (3)$$

Where weekly and monthly realized volatilities are calculated, respectively, as the average of the last week (five days) of daily volatilities and the average of the last month (22 days) of daily volatilities:

$$RV_t^{(w)} = \frac{1}{5}(RV_t^{(d)} + RV_{t-1}^{(d)} + \dots + RV_{t-4}^{(d)}),$$

$$RV_t^{(m)} = \frac{1}{22}(RV_t^{(d)} + RV_{t-1}^{(d)} + \dots + RV_{t-21}^{(d)}),$$

The HAR-RV model assumes the following form:

$$RV_t^{(d)} = \beta_0 + \beta_{RV}^{(d)}RV_{t-1}^{(d)} + \beta_{RV}^{(w)}RV_{t-1}^{(w)} + \beta_{RV}^{(m)}RV_{t-1}^{(m)} + \epsilon_t, \quad (4)$$

For the sake of completeness, we introduce the logarithmic specification of the HAR-RV model, which is constructed using logarithms of the variables from the previous model. This is defined as:

$$\ln(RV_t^{(d)}) = \alpha + \beta_{RV}^{(d)}\ln(RV_{t-1}^{(d)}) + \beta_{RV}^{(w)}\ln(RV_{t-1}^{(w)}) + \beta_{RV}^{(m)}\ln(RV_{t-1}^{(m)}) + \epsilon_t, \quad (5)$$

The logarithmic transformation of the model has one very important property, namely that it clearly ensures that the dependent variable assumes only positive values, which is very convenient because the realized variance is a positive random variable.

Realized volatility series are often modeled with autoregressive fractionally integrated moving average (ARFIMA) models, but Corsi (2009) suggests that these models cannot be easily expanded to multivariate models. We classify the logarithmic realized volatility of a set of exchange rates in the form of the vector v_t .

The specification of the vector HAR is then given by:

$$v_t = \beta_0 + \beta_{RV}^{(d)} v_{t-1|t-1} + \beta_{RV}^{(w)} v_{t-1|t-5} + \beta_{RV}^{(m)} v_{t-1|t-22} + \gamma z_t + \epsilon_t, \quad (6)$$

Where the β values represent the square matrices of coefficients, z_t is a vector of exogenous regressors, and ϵ_t is a vector innovation term. The lagged realized volatility is then defined as:

$$v_{(t-1|t-k)} = \frac{1}{k} \sum_{j=1}^k v_{t-j}, \quad k = 1, 5, 22, \quad (7)$$

The HAR model comprises three volatility components (daily, weekly and monthly) that correspond to the first lag of the logarithmic realized volatility and the normalized sums of the previous 5 days and 22 days logarithmic realized volatilities, respectively. These represent the different reaction times of various market agents to the arrival of news and provide the opportunity to associate volatility over longer intervals to that over shorter intervals. Corsi (2009) proposes that short-term market investors may use the information from long-term volatility to adjust their trading activities, thus causing volatility to increase in the short term.

The HAR model is very attractive for how it describes the interactions of exchange rate volatility over time. The model allows the examination of how long-term volatility influences the expectations of future market trends.

Similar to the work of Bubàk and Zikes (2009), we generalize the multivariate HAR model by allowing the vector innovation term ϵ_t to follow a multivariate GARCH process. We employ the DCC-GARCH model of Engle (2002) in order to capture the second moments of volatility and explore the time-varying correlation of the volatilities in the multivariate case.

We employ the DCC-GARCH model of Engle (2002) to model the dynamics of the innovation process ϵ_t . This offers a generalization of Bollerslev's (1990) Constant Conditional Correlation (CCC-) GARCH model. The variance covariance matrix is defined as:

$$H_t = D_t R_t D_t, \quad (8)$$

Where $D_t = \text{diag}(q_{11,t}^{1/2}, \dots, h_{kk,t}^{1/2})$, $h_{ii,t}$ denotes any univariate GARCH (p, q) process, $i=1, \dots, k$.

We use a particular version of the dynamic conditional correlation models of Engle and Sheppard (2001) and Engle (2002). The conditional matrix is given by the following transformation:

$$R_t = \text{diag}(q_{11,t}^{-1/2}, \dots, q_{KK,t}^{-1/2}) Q_t \text{diag}(q_{11,t}^{-1/2}, \dots, q_{KK,t}^{-1/2}), \quad (9)$$

Where $Q_t = (q_{ij,t})$ follows, $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha\eta_{t-1}\eta'_{t-1} + \beta Q_{t-1}$,

And where $\eta_t = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$ represents the standardized residuals, $\bar{Q} = T^{-1} \sum_{t=1}^T \eta_t \eta_t'$ is a $k \times k$ unconditional variance matrix of η_t , and α and β are non-negative scalars that satisfy the condition that $\alpha + \beta < 1$. This is an autoregressive moving average (ARMA) representation of the conditional correlation matrix that guarantees positive values for Q_t and R_t .

In order to estimate the multivariate DCC-GARCH model, we proceed as follows. We iteratively remove from each equation the least significant variable until all the remaining variables are significant. We then adapt the DCC model to a residuals series. Following Engle and Shepard (2001), we estimate the model in one step to obtain valid standard errors for the DCC estimates.

4. Data

Our analysis is based on intraday, 30-minute spot exchange rate quotes for the EUR/USD, EUR/JPY, EUR/GBP, EUR/CHF and EUR/AUD currency pairs over a period from January 1, 2004 to October 30, 2014. The data were extracted from the Thomson Reuters FX Indices. The 30-minute interval was selected to avoid microstructure noise, based on the work of Andersen et al. (2003). The choice of the five currency pairs was based on their importance to the global forex market, as well as the fact that most studies focus on the volatility of the US dollar despite the importance of the euro to the forex market. We define three distinct periods: January 1, 2004 to June 30, 2007 (the pre-crisis period); July 1, 2007 to December 31, 2011 (the crisis period); and January 1, 2012 to October 19, 2014 (the post-crisis period). This distinction is based on annual reports from the European Central Bank, the Federal Reserve Bank of New York (2009), and other empirical studies (Attinasi et al., 2010; Syllignakis and Kouretas, 2011; Ait-Sahalia et al., 2012; Grammatikos and Vermeulen, 2012). As we will show later, the exchange rate volatility series exhibits different behaviors across the three sample periods.

We compute the intraday returns $r_{i,t}$ from the fluctuations between t and $t+1$. Next, we built 48 intervals of 30 minutes from 21:00 GMT to 21:00 GMT the following day. The realized volatility is then expressed as:

$$RV_T = \sqrt{\sum_{i=1}^{48} r_{i,t}^2}, \quad (10)$$

While the forex market is open 24 hours a day, 7 days a week, transactions during the weekends and holidays are less important. We therefore followed the standard approach of Andersen and Bollerslev (1998) in adjusting the data to avoid the holiday effect. We therefore discarded the weekend periods from Friday 21:00 GMT to Sunday 21:00 GMT, as well as any major public holidays, such as the Christmas period (December 24–26), the New Year period (December 31 to January 2), Memorial Day, Labor Day, and Thanksgiving/Black Friday.

Table 1: Descriptive statistics

		Mean	Standard deviation	Skewness	Excess Kurtosis	Min	Max
Pre-crisis period							
EUR/USD	RV_t	0.256	0.217	3.450	27.769	0.006	2.762
	LRV_t	-1.620	0.721	-0.098	3.385	-4.983	1.016
EUR/JPY	RV_t	0.269	0.342	11.111	194.614	0.018	7.056
	LRV_t	-1.729	0.629	0.336	3.758	-4.005	0.480
EUR/CHF	RV_t	0.050	0.044	5.697	53.318	0.008	0.559
	LRV_t	-3.257	0.563	0.369	3.975	-4.789	-0.688
EUR/GBP	RV_t	0.137	0.196	8.789	102.167	0.010	3.157
	LRV_t	-2.278	0.639	0.697	5.970	-4.541	1.149
EUR/AUD	RV_t	0.311	0.378	9.145	124.72	0.029	6.281
	LRV_t	-1.546	0.606	0.253	3.901	-3.520	1.837
Crisis period							
EUR/USD	RV_t	0.765	0.911	2.467	10.368	0.025	5.602
	LRV_t	-0.917	0.849	0.029	3.334	-3.749	1.856
EUR/JPY	RV_t	1.666	2.828	4.446	31.468	0.038	28.206
	LRV_t	-0.410	0.958	0.459	3.793	-3.253	3.339
EUR/CHF	RV_t	0.336	0.515	5.747	47.372	0.0235	5.258
	LRV_t	-1.852	1.292	-0.191	3.619	-7.522	3.896
EUR/GBP	RV_t	0.336	0.687	2.390	10.293	0.042	4.840
	LRV_t	-1.225	0.822	0.255	3.572	-3.804	1.576
EUR/AUD	RV_t	1.545	3.398	8.309	96.090	0.085	47.063
	LRV_t	-0.768	0.890	0.975	4.852	-2.956	3.851
Post-crisis period							
EUR/USD	RV_t	0.373	0.358	4.897	63.220	0.007	6.401
	LRV_t	-1.850	0.839	-0.178	3.069	-4.952	0.874
EUR/JPY	RV_t	0.702	1.027	9.893	161.636	0.014	22.093
	LRV_t	-1.163	0.928	-0.183	3.179	-8.672	-0.213
EUR/CHF	RV_t	0.238	1.410	29.917	118.050	0.0001	49.245
	LRV_t	-3.994	1.605	-0.584	3.143	-8.672	-0.213
EUR/GBP	RV_t	0.294	0.237	4.712	44.442	0.014	3.443
	LRV_t	-2.098	0.717	0.208	3.200	-4.224	0.343
EUR/AUD	RV_t	0.372	0.374	7.238	105.826	0.027	7.434
	LRV_t	-1.462	0.697	0.128	3.086	-3.594	0.706

Table 1 shows descriptive statistics for the daily realized volatilities and logarithmic realized volatilities (LRV), separated for each data period. The skewness coefficients are generally not zero and positive, indicating a right-skewed

distribution for most of the series during the three sample periods. However, the coefficient is negative for the first period of the logarithmic realized volatilities of EUR/USD and EUR/CHF. During the second period, it is negative for the logarithmic realized volatilities of EUR/USD, EUR/JPY and EUR/CHF, indicating a left-skewed distribution.

During the three periods, the excess kurtosis indicates a leptokurtic distribution with values concentrated around the mean and fat tails in the case of all series. Jarque-Bera statistics confirm the rejection of the normality hypothesis for all series, indicating nonlinear behavior.

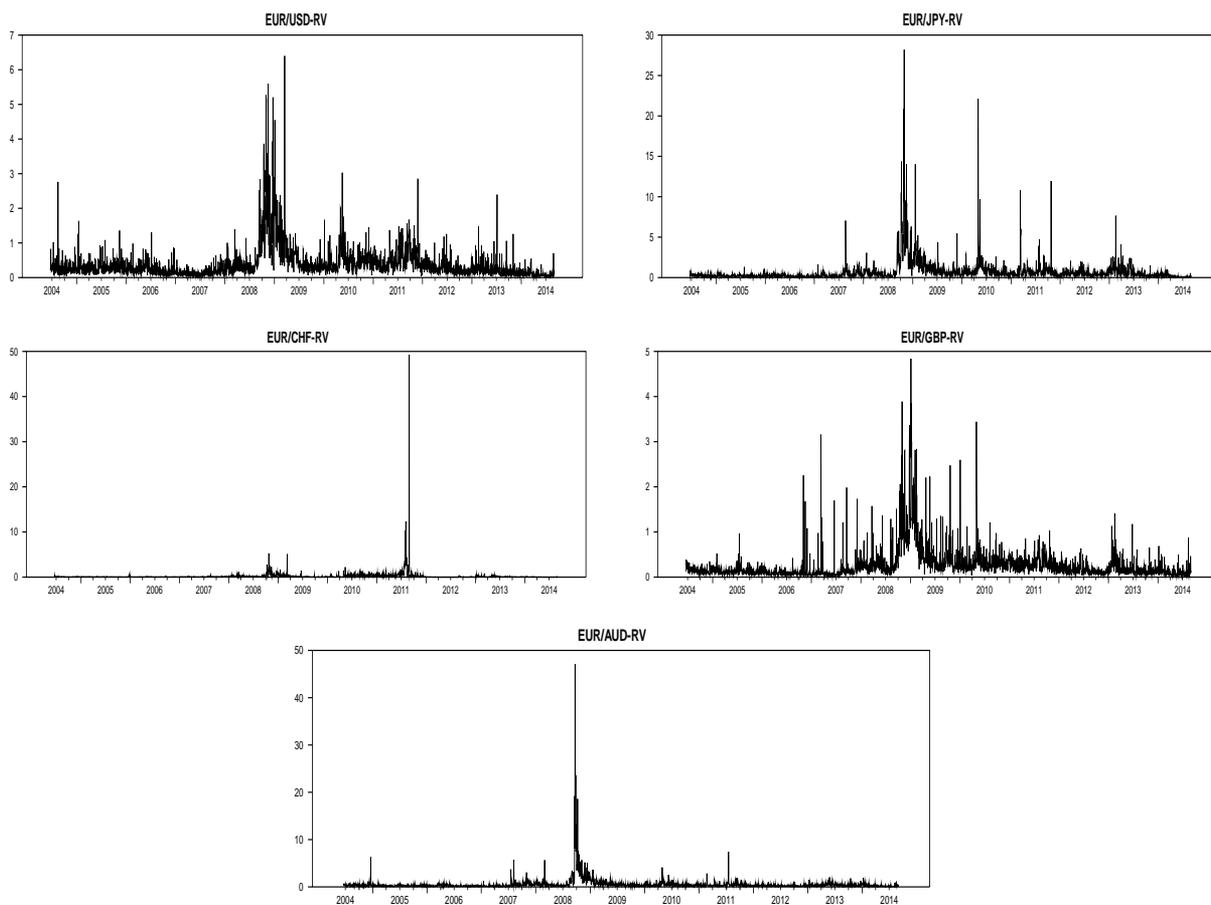


Figure 1: Plots of daily realized volatility (RV).

Figure 1 shows plots for daily EUR/USD, EUR/JPY, EUR/GBP, EUR/CHF, and EUR/AUD realized volatilities for the entire sample period. The subprime crisis of 2008, followed by the sovereign debt crisis in the Eurozone, led to substantial spikes in volatility for forex exchange rates. It is noteworthy how the overall pattern follows the important events that the currencies experienced since 2004.

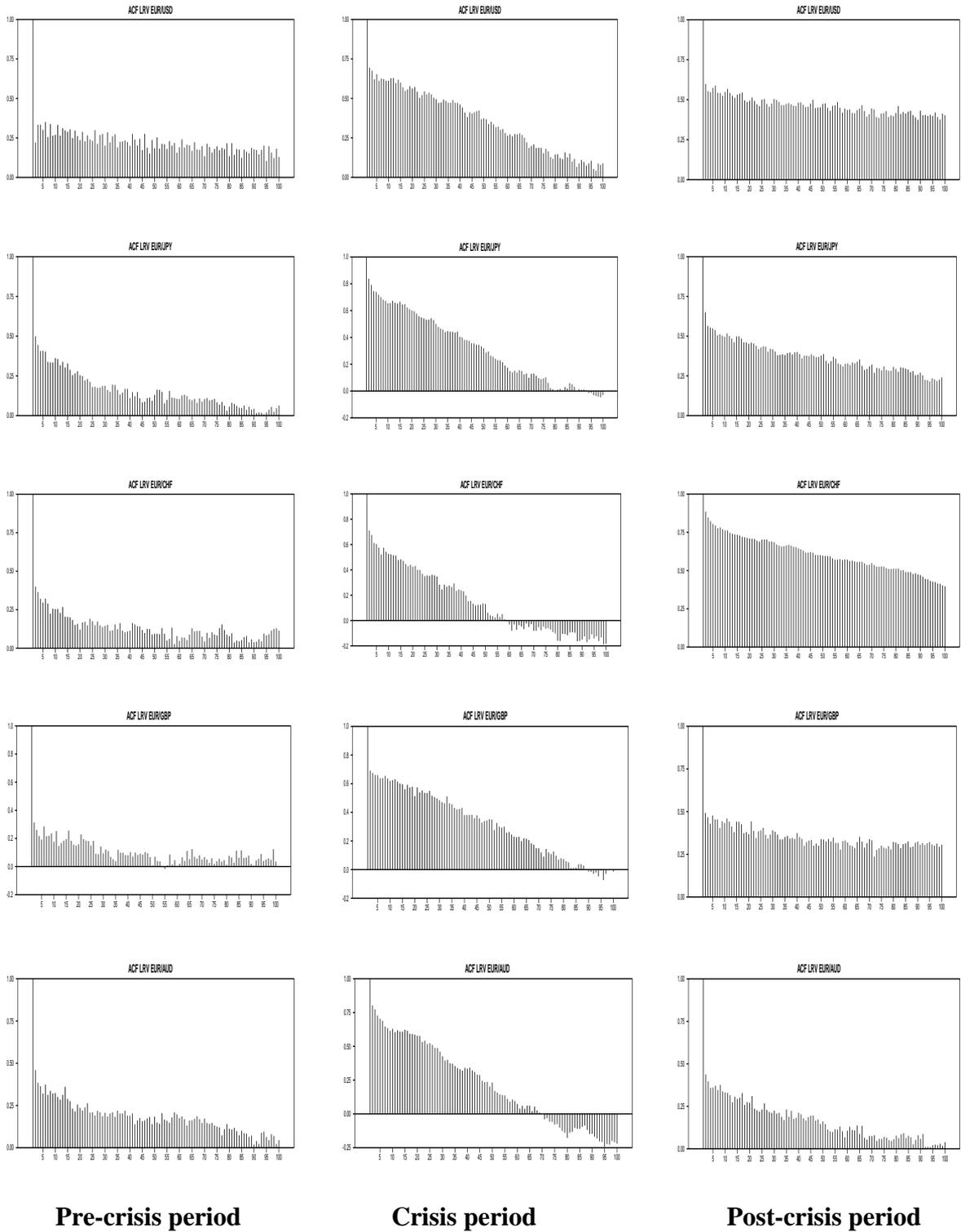


Figure 2: Autocorrelation plots for daily logarithmic realized volatility (LRV)

Figure 2 shows the autocorrelation functions of the logarithmic realized volatilities. During the pre-crisis period, the autocorrelation function (ACF) of LRV shows slow decays, indicating a very persistent process consistent with long-memory dynamics. In addition, during the crisis period, the ACF of LRV exhibits less slow decays. This could be explained by the fact that the crisis significantly affected the long-memory property of the series.

During the post-crisis period, the autocorrelation functions decayed more slowly than during the second period. We can attribute this difference between the three sample periods to differences in volatility transmissions.

5. Main Results

As was found from the autocorrelation analysis, the series involved behaved differently during the three sample periods. We therefore analyzed volatility transmission separately for the periods from January 1, 2004 to June 30, 2007 (the pre-crisis period); the period from July 1, 2007 to December 31, 2011 (the crisis period), and the period from January 1, 2012 to October 19, 2014 (the post-crisis period).

5.1 Granger causality tests

The causal relationships between currency pairs provide a better understanding of the structure of the transmissions between volatilities on the forex market. We therefore carried out Granger causality tests based on a full multivariate system that includes all five currencies. Table 2 reports the Granger causality test results for the three sample periods.

Table 2: Granger causality tests

Pre-crisis period						Crisis period					Post-crisis period				
LRV_t	JPY	CHF	GBP	AUD	USD	JPY	CHF	GBP	AUD	USD	JPY	CHF	GBP	AUD	USD
JPY	- (0.007)	1.205 (0.235)	3.548** (0.000)	1.345 (0.133)	3.436** (0.000)	-	0.705 (0.837)	2.841** (0.000)	0.828 (0.691)	23.296** (0.000)	-	0.667 (0.872)	1.334 (0.140)	1.043 (0.407)	12.075** (0.000)
CHF	1.918* (0.007)	-	1.637** (0.033)	0.919 (0.569)	2.841** (0.000)	9.201** (0.000)	-	2.800** (0.000)	0.336 (0.998)	8.011** (0.000)	2.564* (0.000)	-	3.153* (0.000)	1.344 (0.134)	5.937* (0.000)
GBP	1.120 (0.318)	0.876 (0.627)	-	0.744 (0.795)	1.417** (0.097)	0.825 (0.692)	0.978 (0.489)	-	0.639 (0.897)	10.498** (0.000)	5.739** (0.000)	1.221** (0.221)	-	0.848 (0.664)	20.265** (0.000)
AUD	1.486** (0.070)	1.561** (0.049)	1.509** (0.063)	-	1.860** (0.009)	9.418** (0.000)	4.073** (0.000)	3.294*** (0.000)	-	4.950** (0.000)	7.707** (0.000)	2.285* (0.000)	5.232* (0.000)	-	7.083* (0.000)
USD	0.958 (0.517)	0.811 (0.713)	3.243** (0.000)	1.221 (0.220)	-	1.446** (0.083)	0.929 (0.555)	2.223** (0.001)	0.695 (0.847)	-	2.927** (0.000)	1.048 (0.401)	1.073 (0.371)	1.042 (0.408)	-

Note : The table show the F-values for the Granger causality tests. The corresponding p-values of the F-statistics are shown in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

During the pre-crisis period, we observe how the realized volatility of EUR/JPY is influenced by the realized volatility of EUR/CHF and EUR/AUD. The EUR/CHF volatility, meanwhile, is caused only by the volatility of EUR/AUD. The EUR/GBP and the EUR/USD volatilities, in contrast, are influenced by all exchange rate volatilities. On the other hand, a causal relationship exists between the EUR/GBP and the EUR/USD volatilities. The EUR/AUD volatility does not react to any exchange rate volatility, which could be explained by the fact that the Australian dollar is driven by the country's booming mining sector. Indeed, the Australian economy has for several years benefited from the strong demand from emerging countries for the raw materials that Australia produces and exports. The considerable geographical separation of Australia from the Eurozone could also be a considerable factor.

During the crisis period, the Granger causality test results show a more significant relationship when compared to the pre-crisis period. The subprime crisis that hit the US stock market was subsequently transmitted to the European stock market and then the forex market. EUR/AUD volatility causes EUR/GBP volatility, but EUR/JPY volatility no longer affects the EUR/CHF volatility. In addition, the Australian dollar is still a little sensitive in relation to other currencies, accelerating the influence of EUR/AUD volatility during this period. This may be the consequence of a period of uncertainty in the financial market and the result of two successive crises rather than the presence of a causal effect on the forex market. In general, increased volatility in the foreign exchange market is often seen as a sign of greater uncertainty in the financial market. The causal relationship between the EUR/USD and EUR/JPY volatilities persists during the second period and increases in intensity.

During the post-crisis period, the coefficients of the Granger causality tests increased. This may be due to persistent uncertainty in the forex market, which had been further amplified by the sovereign debt crisis in the Eurozone. We note that the volatilities of EUR/JPY and EUR/USD were affected by all the other volatilities involved. During this period, the EUR/GBP volatility is only influenced by the EUR/CHF and EUR/AUD volatilities, while the EUR/USD volatility did not influence the EUR/GBP volatility. The EUR/CHF volatility is affected by the EUR/GBP and EUR/AUD volatilities, and the relationship between the EUR/AUD and EUR/JPY volatilities remains continuous.

The Granger causality test results show the presence of a dynamic correlation between the different exchange rate volatilities present in the forex market.

5.2 Volatility transmission model

In order to understand the pattern of volatility transmission, we estimated the multivariate HAR-RV model.

The estimation results are reported in table 3. The first equation corresponds to the EUR/JPY volatility, which is affected by its own short-term and medium-term components, as well as by the medium-term volatility component of EUR/USD. The EUR/JPY volatility is slightly sensitive to disturbance in the American market, but it seems insensitive to disturbances in the European market.

The results for the EUR/CHF equation reveal that volatility is positively influenced by its own volatility and the EUR/AUD short-term and medium-term components. The medium-term volatility component of EUR/USD also influences EUR/CHF volatility. This is consistent with the fact that during calmer periods, the volatility of EUR/CHF correlates with EUR/USD volatility.

The EUR/GBP volatility is affected in the short-term by its own volatility component and that of EUR/JPY. In the medium term, it is affected by its own volatility component but also by the volatility components of all the exchange rates, with a particularly adverse effect from EUR/AUD and EUR/USD volatilities. In line with the findings of Antonakakis (2012), it seems that the EUR/GBP is the dominant receiver of volatility.

As for the EUR/AUD equation, we note how it is influenced by its own long-term volatility component. In the short and the medium term, we observe a volatility transmission from EUR/USD volatility.

In the EUR/USD equation, we can see that in addition to its own short-term and medium-term volatility components, the long-term volatility component of EUR/AUD affects the present volatility of EUR/USD with a negative influence. The volatility transmission between the US and the Australian dollars can be explained by the fact that these two currencies strongly correlate to the evolution of the materials sector (e.g., iron, uranium, coal). This is especially true for gold, because Australia is considered the third-largest producer in the world. Furthermore, there is a small negative effect from the short-term component of EUR/GBP. During the pre-crisis period, the volatility transmission from EUR/USD to all other exchange rates demonstrates a strong role for the medium-term volatility component.

The crisis period (the subprime crisis and the subsequent sovereign debt crisis) negatively affected several countries in the Eurozone. The volatility in the forex market consequently increased. The results differ in terms of magnitude and sign from the pre-crisis period. For EUR/JPY, we note how this volatility is affected in the short term by its own volatility component and that of the EUR/GBP. In the medium term, we see how this volatility is influenced by its own component and the volatility component of EUR/USD. However, the results suggest that there is no volatility transmission in the long term.

The EUR/CHF volatility is positively influenced in the short term by its own volatility component and that of EUR/USD. In contrast to the first period, the

EUR/CHF volatility is negatively affected by the long-term volatility component of EUR/AUD.

The estimation results for the EUR/GBP volatility suggest that there is transmission of volatility in the short term from its own volatility component but also from the volatility components of EUR/JPY and EUR/CHF. It is also influenced in the medium term by the volatility components of EUR/CHF and EUR/USD. The volatility of EUR/AUD no longer influences the EUR/GBP. However, we observe a strong reaction in the volatility of EUR/GBP from the weekly component of EUR/USD. This demonstrates the significant impact that the US market has on other financial markets. It could also be explained by the strong economic and political links between the United States and Great Britain.

Table 3: Estimation results HAR-RV

LRV _t	Pre-crisis period					Crisis period					Post-crisis period				
	JPY	CHF	GBP	AUD	USD	JPY	CHF	GBP	AUD	USD	JPY	CHF	GBP	AUD	USD
β_0	0.212 (0.72)	-1.17** (-4.44)	-0.261 (-0.922)	-0.255 (-0.89)	0.122 (0.399)	0.118** (2.202)	-0.077 (-1.087)	-0.13** (-2.22)	-0.15** (-2.53)	0.026 (0.597)	0.287** (1.911)	-0.602 (-2.822)	-0.45** (-2.87)	-0.111 (-0.688)	-0.268** (-1.934)
$\beta_{JPY}^{(d)}$	0.14** (4.08)		0.073** (2.096)		0.258** (6.847)	0.334** (11.30)		0.052** (1.929)		0.407** (16.41)	0.267** (7.547)				0.530** (15.234)
$\beta_{JPY}^{(w)}$	0.17** (2.76)					0.072** (2.057)				-0.05** (-1.94)	0.062** (3.934)				-0.047** (-3.069)
$\beta_{JPY}^{(m)}$				0.064** (1.706)							0.016** (3.401)			0.071** (1.721)	
$\beta_{CHF}^{(d)}$		0.148** (4.115)					0.413** (14.02)	0.086** (3.795)				0.568** (14.82)	0.174** (9.479)		-0.044** (-1.779)
$\beta_{CHF}^{(w)}$			0.068** (1.689)					0.066** (2.468)				-0.04** (-4.561)	-0.03** (-5.432)		-0.060** (-1.938)
$\beta_{CHF}^{(m)}$															-0.005** (-2.873)
$\beta_{GBP}^{(d)}$			0.157** (4.329)		-0.07** (-1.88)	0.189** (6.622)		0.163** (5.542)			0.372** (10.78)	-0.11** (-2.327)	0.077** (2.030)		0.063** (1.896)
$\beta_{GBP}^{(w)}$			0.108** (2.881)					0.051** (1.666)		0.045** (4.201)	-0.03** (-1.903)		0.070** (1.692)		0.066** (3.863)
$\beta_{AUD}^{(d)}$		0.077** (2.297)		0.164** (4.548)					0.318** (10.78)					0.144** (3.735)	
$\beta_{AUD}^{(w)}$			-0.07** (-2.17)	0.144** (3.897)					0.087** (8.230)		-0.06** (-1.712)		-0.06** (-1.798)	0.060** (3.583)	-0.067** (-2.031)
$\beta_{AUD}^{(m)}$					-0.08** (-1.975)		-0.07** (-1.956)		0.059** (1.835)					0.022** (3.997)	
$\beta_{USD}^{(d)}$				0.058** (1.750)	-0.07* (-1.95)		0.109** (1.921)			0.229** (7.717)		-0.11** (-1.974)			0.074** (1.962)
$\beta_{USD}^{(w)}$	-0.06* (-1.8)	-0.09** (-2.97)	-0.07** (-2.20)		0.113** (3.042)	-0.04** (-2.833)		0.036** (2.692)		0.089** (7.974)	-0.07** (-1.788)	0.128** (2.130)		0.035** (1.968)	0.037** (2.216)
$\beta_{USD}^{(m)}$									0.075** (2.402)						0.017** (2.966)
R ²	0.246	0.186	0.333	0.341	0.352	0.657	0.668	0.512	0.552	0.676	0.638	0.783	0.448	0.331	0.571

DCC estimation															
α	0.12** (6.10)	0.226** (4.316)	0.222 (1.838)	0.154** (3.860)	0.226** (2.568)	0.185 (0.396)	0.245 (2.528)	0.187 (0.758)	0.037** (5.722)	0.537** (4.429)	0.062** (3.181)	0.393** (4.171)	0.069** (4.289)	0.031** (6.125)	0.204** (3.058)
β	0.99** (284)	0.919** (23.53)	0.966** (22.05)	0.976** (115.4)	0.628** (2.192)	0.815** (5.896)	0.695** (5.280)	0.977** (14.09)	0.968** (123.2)	0.533** (2.592)	0.923** (36.38)	0.522** (4.387)	0.899** (38.98)	0.960** (119.3)	0.972** (47.20)
d_1	0.01** (2.14)	0.050** (2.176)	0.060** (1.841)	0.022** (1.900)	0.016** (2.915)	0.028** (4.082)	0.091** (1.213)	0.019** (4.190)	0.043** (2.405)	0.018** (3.424)	0.024** (1.854)	0.005 (1.112)	0.052** (3.390)	0.028** (1.649)	0.015** (1.882)
d_2	0.98** (84.3)	0.866** (13.26)	0.927** (18.62)	0.958** (52.000)	0.984** (147.9)	0.942** (49.76)	0.856** (5.456)	0.950** (58.53)	0.871** (17.53)	0.967** (102.2)	0.954** (54.07)	0.972** (63.51)	0.917** (35.67)	0.930** (18.62)	0.981** (74.19)
LogL	-634.08	-565.97	-587.42	-602.91	-688.78	-1065.9	-1291.7	-967.85	-996.06	-743.54	-565.23	-773.89	-634.35	-566.08	-434.31

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

The current volatility of EUR/AUD was affected during this period by all of its own volatility components. In the long term, we see volatility transmission from EUR/USD. In contrast, during the crisis period, the volatility of EUR/AUD seems mostly unresponsive to any foreign component other than EUR/USD.

The current volatility of EUR/USD is influenced in the short and medium term by its own volatility components. Furthermore, the short-term results show an effect coming from the volatility component of EUR/JPY. In the medium term, there is a volatility transmission from EUR/GBP and EUR/JPY, so an increase in realized volatility in the British market is accompanied by increased realized volatility for other forex rates. This implies the presence of transmission channels that allow the British market to positively transmit volatility to other markets. This supports the results of the Granger causality tests, which showed causal links between EUR/USD and EUR/GBP during the crisis period. Furthermore, during the crisis period, the EUR/USD volatility influences the volatilities of all other exchange rates.

In addition, the results show exchange rates to be more responsive to their own short-term volatility components. There is therefore a high persistence level for volatility in the foreign exchange market. Short- and medium-term investors dominate the forex market and exert a great influence on forex realized volatility. Before the crisis, the short-term volatility component was not of major importance, but during the crisis period, this component constituted one source of long-term volatility variability. What is more, in turbulent financial periods characterized by high levels of uncertainty, the short-term volatility component plays a very important role in explaining volatility in the long term and its transmission through the forex market. In addition, the long-term components are relatively insignificant due to long-term investors tending to shun the forex market.

During crisis periods, markets become more volatile and traders tend to react very quickly to any new information disclosed to the market. High volatility can generate gains for investors in short-term positions, but investors taking long-term positions prefer less volatility. In reality, financial crises of varying natures and causes touch the foreign exchange market, especially with regards to investor behavior. This may be explained by the financial liberalization, economic globalization, and deregulation that took place in the 1980s.

Crisis effects persist in the post-crisis period, with the coefficients increasing due to the impact of the sovereign debt crisis. The EUR/JPY volatility is influenced by all of its own volatility components, and we observe volatility transmission in the short and medium term from EUR/GBP. In the medium term, the EUR/JPY volatility is also influenced by the volatility components of EUR/AUD and EUR/USD.

The EUR/CHF volatility is influenced in the short and medium term by all of its own volatility components. It is also affected by the short-term volatility components of EUR/AUD and EUR/USD.

However, the EUR/GBP volatility is affected in the short term by its own volatility and by the EUR/CHF volatility components. In the medium term, it is influenced by its own component and by the volatility components of EUR/CHF and EUR/AUD. The EUR/USD volatility no longer influences the EUR/GBP volatility,

however. Prior to the crisis period, the EUR/GBP volatility had less impact in terms of transmission, but during the crisis and after the crisis period, the EUR/GBP volatility was transmitted to the other major currencies and became significant during the post-crisis period. The increasing GBP volatility may be explained by Moody's rating downgrade for the UK.

The volatility transmission for EUR/AUD is similar to that of the preceding periods, with the exception of EUR/JPY in the long term.

Comparing the two previous periods, the EUR/USD volatility is influenced by all exchange rate volatilities. The EUR/JPY volatility plays an important role in explaining the current EUR/USD volatility in the short term, while the EUR/JPY, EUR/GBP, and EUR/AUD volatilities influence the EUR/USD volatility in the medium term.

The effects of volatility transmission persist into the post-crisis period. Hence, we find that volatility transmission between exchange rates differs significantly over the three sample periods. In addition, the short-term components have less of an impact outside the crisis period.

However, the differences observed during the three periods may have resulted from heterogeneity in investors' feelings before, during, and after the crisis. There is therefore volatility transmission between almost all the exchange rates involved over the three horizons (the short, medium, and long term).

Table 3 shows the DCC estimation applied to the HAR-RV residuals. Parameters α and β correspond to the estimated ARCH and GARCH effects for each equation of the multivariate HAR-RV model. The estimation results indicate a high persistence of shocks during the three sample periods, revealing a slow convergence toward a state of equilibrium. The results of the DCC-GARCH (1.1) model show that the parameters d_1 and d_2 are significant and satisfy the non-negativity. The sum of the parameters is close to the unity $d_1 + d_2 < 1$, implying persistent correlations, with a rather small news parameter d_1 and slow decay d_2 (Engle and Sheppard, 2001). The results also show a time-varying correlation structure.

Figure 3 shows strong evidence of increasing instantaneous correlation between the different exchange rates during the crisis period. The conditional correlations between different volatilities are not constant, and during the first period, the correlation between exchange rates' realized volatilities varied between -0.2 and 0.3. During the second period, the correlation increased to 0.5 and 0.6 for the different exchange rate pairs. With the exception of GBP/USD and GBP/JPY, the correlations increased to approach 0.8 and 0.9, respectively.

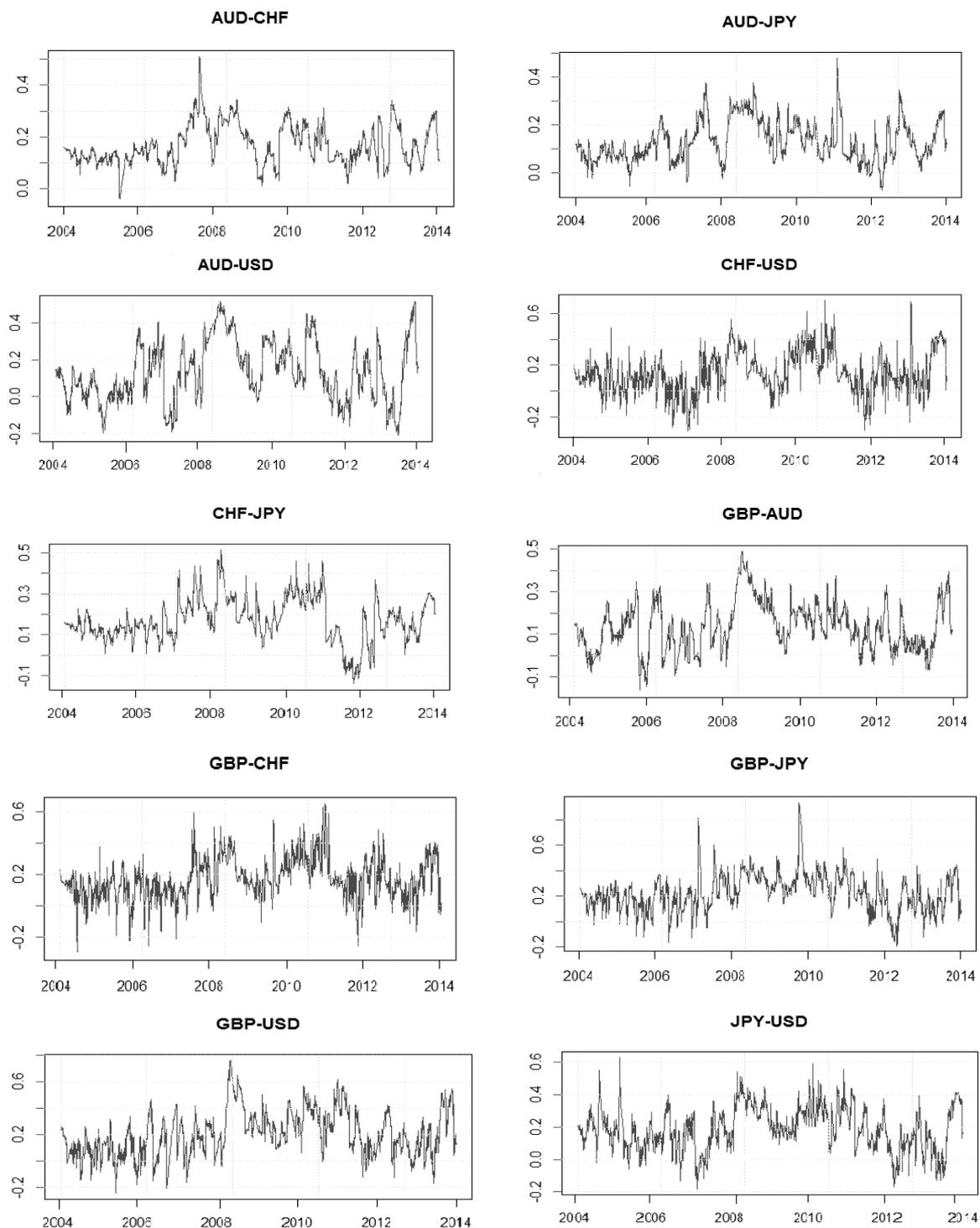


Figure 3: Conditional correlations implied by the DCC-GARCH model

The third period was marked by a slight decline with a fresh rise at the beginning of 2012. These findings show a high degree of integration between these currencies in the forex market and indicate persistent effects due to volatility transmission.

6. Conclusion

In this study, we analyzed the dynamics of volatility transmission in the foreign exchange market. We used high-frequency data to construct realized volatility and allow for a more current estimation of volatility. By using the multivariate extension of HAR-RV as proposed by Corsi (2009), this model is able to take account of volatility transmission with daily, weekly, and monthly horizons, thus allowing for a greater understanding of the origins of any observed volatility transmission. This would not have been the case with the multivariate GARCH framework

The results provide evidence for the existence of volatility transmission between exchange rates in the forex market. During the pre-crisis period, we observe volatility transmission from EUR/USD to all the other exchange rates, with a significant effect coming from medium-term volatility components.

During the crisis period, exchange rate volatility increased in the forex market. The results show how the EUR/USD volatility influences the forex market, with a significant impact from its short-term volatility components. This increase in the short-term relationship seems to indicate a generally faster reaction from the market to volatility dynamics. During the crisis, the increased uncertainty in the markets is reflected by the importance of the short-term volatility components. In addition, investors who act in the short and medium term have more influence on volatility in the forex market due to the feelings of uncertainty that dominate the market. During the post-crisis period, the results show a persistence of volatility transmission, and the volatility components of EUR/GBP become more significant. The movement of exchange rate volatility has a global impact, because the forex market is a global one. It is a market characterized by an expansive information flow, and it has a very high degree of integration, especially for major currencies. In general, volatility can be considered a consequence of monetary policies, which are surrounded by a degree of uncertainty and have an important impact on the volatility of exchange rates. Due to the differences and unique characteristics of the forex market, volatility transmission between currencies can spread and affect investors' currency portfolios in a less intuitive way. According to Kanas and Kouretas (2001) and Greenwood-Nimmo et al. (2016), the positive and significant effects of volatility can increase the risk of reduced gains from international portfolio diversification. Likewise, Amonlirdviman and Carvalho (2010) explicitly show that volatility transmission reduces the gains from the diversification of international portfolios and amplifies their variability. It therefore seems sensible to understand the phenomenon of volatility transmission in the forex market. The major currencies in the foreign exchange market exhibit similar volatility behaviors, although the EUR/USD exchange rate has dominant effects in terms of transmission.

Volatility transmission in the foreign exchange markets implies the existence of a dependency in variance, reflecting the inefficiency of markets and the heterogeneity of investors, which in turn allows for risk forecasting.

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