Long Memory and Asymmetric Effects between Exchange Rates and Stock Returns

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Abstract

The analysis of time varying correlation between stock prices and exchange rates in the context of international investments has been well researched in the literature in last few years. In this paper we study the interdependence of US dollar exchange rates expressed in euro (EUR) and three major stock prices (Nikkei225, SSE and MSCI). Focusing on different phases of the Global financial crisis (GFC) and the Euro zone Sovereign Debt Crisis (ESDC), we adopt a multivariate asymmetric dynamic conditional correlation EGARCH framework and the DCC model into a multivariate fractionally integrated APARCH framework (FIAPARCH-DCC), during the period spanning from January 1, 2000 until December 10, 2013. The empirical results suggest asymmetric responses in correlations among the three stock prices and exchange rate, a high persistence of the conditional correlation (the volatility displays a highly persistent fashion) and the dynamic correlations revolve around a constant level and the dynamic process appears to be mean reverting.

Moreover, the results indicate an increase and a decrease of exchange rates and stock prices correlations during the crisis periods, suggesting the different vulnerability of the currencies. Finally, we find some significant decreases and increase in the estimated dynamic correlations, indicating existence of a "currency contagion effect" during turmoil periods.

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1 Introduction

Unlike past crises, such as the 1997 Asian financial crisis, the 1998 Russian crisis and the 1999 Brazilian crisis, the recent 2007-2009 global financial crisis originated from the largest and most influential economy, the US market, and was spreading over the other countries' financial markets worldwide. Global financial crisis resulted in sharp declines in asset prices, stock and foreign exchange markets, and skyrocketing of risk premiums on interbank loans. It also disrupted country's financial system and threatened real economy with huge contractions.

In the economic theory, interaction between foreign exchange market and stock market is analysed through two theoretical approaches: the "stock oriented" approach (e.g. Branson, 1983; Frankel, 1983) and the "flow oriented" approach (e.g. Dornbush and Fisher, 1980). In the first approach, the foreign exchange rate is determined by the demand and supply of financial assets such as equities and bonds. In the second approach, the exchange rate is determined by a country's current account balance or trade balance. Flow oriented models provides a positive interaction between stock price and foreign exchange rate.

In the literature, a positive relationship between the stock prices and exchange rate may result from a real interest rate disturbance as the real interest rises, the exchange rate falls and the capital inflow increases (Wu, 2001).

On the other hand the theory of arbitrage suggests that a higher real interest rate causes the stock prices to fall and decrease the present value of the firms' future cash-flows .Changes in the exchange rate affects the international competitiveness of countries where exports are strong and fluctuations in foreign exchange rates can lead to substantial changes in the relative performance of equity portfolios, when expressed in a common currency (Malliaropulos, 1998).

Number of studies that attempt to examine the effect on stock prices of exchange rates, however, the findings are not uniform (Ibrahim, 2000). Some studies give evidence of negative effects on exchange rates on stock markets (Soenen and Henningar, 1988), while others found positive effects (Aggarwal, 1981). Other studies contribute this results and find that the exchange rate changes have no significant impact on the stock market (Solnik, 1984). Thus, the existing literature provides mixed results when analysing the relationship between stock prices and exchange rate.

In the financial econometrics literature, it has been well documented that stock market volatility and exchange rate increases more after a negative shock than after a positive shock of the same size. This asymmetry in stock market and exchange rate volatility has been extensively examined within univariate GARCH models (see Engle and Ng (1993)).

The empirical evidence on the stock price – exchange rate relationships has been document by numerous studies. For example, Yang and Doong (2004) find that stock market movements have a significant effect on future exchange rate changes for the G7 countries over the period 1979-1999. Pan et al. (2007) use a VAR approach to analyze the interaction between stock markets and exchange markets for seven East Asian countries, and provide evidence of a significant bidirectional relationship between these markets before the Asian financial crisis. More recently, Chkili et al. (2011) use a Markov-Switching EGARCH model to analyze the dynamic relationships between exchange rates and stock returns in four emerging countries (Singapore, Hong Kong, Mexico and Malaysia) during both normal and turbulent periods. They provide evidence of regime dependent links and asymmetric responses of stock market volatility to shocks affecting foreign exchange market.

Our research employ a Markov-Switching EGARCH model to investigate the dynamic linkage between stock price volatility and exchange rate changes for four emerging countries over the period 1994–2009 (Chkili et al. (2011). Results distinguish between two different regimes in both the conditional variance and conditional mean of stock returns. Our results provide that foreign exchange rate changes have a significant impact on the probability of transition across regimes.

To examine the impact on stock prices of exchange rates, we employed cross-correlation function approach (see Inagaki, 2007), vector autoregressive model and Granger causality tests (see Nikkinen et al., 2006), copulas with and without regime-switching (see Patton, 2006; Boero et al., 2011), nonparametric approaches (see Rodriquez, 2007; Kenourgios et al., 2011) and multivariate GARCH processes (see Perez-Rodriquez, 2006; Kitamura, 2010; Dimitriou and Kenourgios, 2013; Tamakoshi and Hamori, 2014). However, most of these previous studies do not address how the interdependence between stock prices and exchange rates was affected by the recent global financial and European sovereign debt crises. The main objective of this work is to explore the asymmetric dynamics in the correlations among exchange rates and stock prices, as this remains under explored in empirical research.

This paper focuses on the impact of the US dollar exchange rates expressed in (EUR) to three stock markets namely NIKKEI225, SSE and MSCI. Specifically, we empirically investigate the asymmetric effect of daily US dollar exchange rate, namely (EUR) about the major stock market returns from January 01, 2000 until December 10, 2013. We use a FIAPARCH model into an univariate fractionally integrated APARCH framework and the multivariate asymmetric DCC (A-DCC) model put forward by Cappiello et al. (2006) to investigate the asymmetric behavior of dynamic correlations among exchange rate and stock prices.

The flexibility feature represents the key advantage of the FIAPARCH model of Tse (1998) since it includes a large number of alternative GARCH specifications. Specifically, it increases the flexibility of the conditional variance specification by allowing an asymmetric response of volatility to positive and negative shocks and long-range volatility dependence. In addition, it allows the data to determine the power of returns for which the predictable structure in the volatility pattern is the strongest (see Conrad et al., 2011). Although many studies use various multivariate GARCH models in order to estimate DCCs among markets during financial crises (see Chiang et al., 2007; Celic, 2012; Kenourgios et al., 2011), the forecasting superiority of FIAPARCH on other GARCH models is supported by Conrad et al. (2011), Chkili et al. (2012) and Dimitriou and Kenourgios (2013). The A-DCC model allows for conditional asymmetries in covariance and correlation dynamics, thereby enabling to examine the presence of asymmetric responses in correlations during periods of negative shocks. Finally, we evaluate how the global financial and European sovereign debt crises influenced the estimated DCCs among the foreign exchange rate and stock markets.

The layout of the present study is as follows. Section 2 presents the empirical methodology. Section 3 provides the data and a preliminary analysis. The empirical results are displayed, analyzed and discussed in section 4. In section 5, we analyzethe DCC behavior during different phases of the global financial and European sovereign debt crises, while section 6 reports the concluding remarks.

2   Econometric Methodology

2.1. Univariate FIAPARCH Model

The AR(1) process represents one of the most common models to describe a time series r_t of stock returns and foreign exchange rate. Its formulation is given as

$$(1 - \xi L)r_t = c + \varepsilon_t, \quad t \in \mathbb{N} \tag{1}$$

with

$$\varepsilon_t = z_t\sqrt{h_t} \tag{2}$$

where $|c| \in [0, +\infty[$, $|\xi| < 1$ and $\{z_t\}$ are independently and identically distributed $(i.i.d.)$ random variables with $E(z_t) = 0$. The variance h_t is positive with probability equal to unity and is a measurable function of Σ_{t-1}, which is the $\sigma -$algebra generated by $\{r_{t-1}, r_{t-2}, \dots\}$. Therefore, h_t denotes the conditional variance of the returns $\{r_t\}$, that is:

$$E[r_t/\Sigma_{t-1}] = c + \xi r_{t-1} \tag{3}$$
$$Var[r_t/\Sigma_{t-1}] = h_t \tag{4}$$

Tse (1998) uses a FIAPARCH(1,d,1) model in order to examine the conditional heteroskedasticity of the yen-dollar exchange rate. Its specification is given as

$$(1 - \beta L)\left(h_t^{\delta/2} - \omega\right) = [(1 - \beta L) - (1 - \phi L)(1 - L)^d](1 + \gamma s_t)|\varepsilon_t|^\delta \tag{5}$$

where $\omega \in [0, \infty[$, $|\beta| < 1$, $|\phi| < 1$, $0 \le d \le 1$, $s_t = 1$ if $\varepsilon_t < 0$ and 0

otherwise, $(1 - L)^d$ is the financial differencing operator in terms of a hypergeometric function (see Conrad et al., 2011), γ is the leverage coefficient, and δ is the power term parameter (a Box-Cox transformation) that takes (finite) positive values. A sufficient condition for the conditional variance h_t to be positive almost surely for all t is that $\gamma > -1$ and the parameter combination (ϕ, d, β) satisfies the inequality constraints provided in Conrad and Haag (2006) and Conrad (2010).When $\gamma > 0$, negative shocks have more impact on volatility than positive shocks.

The advantage of this class of models is its flexibility since it includes a large number of alternative GARCH specifications. When $d = 0$, the process in Eq. (5) reduces to the APARCH(1,1) one of Ding et al. (1993), which nests two major classes of ARCH models. In particular, a Taylor/Schwert type of formulation (Taylor, 1986; Schwert, 1990)is specified when $\delta = 1$, and a Bollerslev(1986) type is specified when $\delta = 2$.When $\gamma = 0$and $\delta = 2$, the process in Eq. (5) reduces to the $FIGARCH(1, d, 1)$ specification (see Baillie et al., 1996; Bollerslev and Mikkelsen, 1996) which includes Bollerslev's (1986) GARCH model (when $d = 0$) and the IGARCH specification (when $d = 1$) as special cases.

2.2. Multivariate FIAPARCH Model with Dynamic Conditional Correlations

In what follow, we introduce the multivariate FIAPARCH process (M-FIAPARCH) taking into account the dynamic conditional correlation (DCC) hypothesis (see Dimitriou et al., 2013) advanced by Engle (2002). This approach generalizes the Multivariate Constant

Conditional Correlation (CCC) FIAPARCH model of Conrad et al. (2011). The multivariate DCC model of Engle (2002) and Tse and Tsui (2002) involves two stages to estimate the conditional covariance matrix H_t. In the first stage, we fit a univariate FIAPARCH (1,d,1) model in order to obtain the estimations of $\sqrt{h_{iit}}$. The daily stock returns and exchange rate are assumed to be generated by a multivariate AR (1) process of the following form:

$$Z(L)r_t = \mu_0 + \varepsilon_t \tag{6}$$

where

- $\mu_0 = [\mu_{0,i}]_{i=1,\dots,n}$: the N −dimensional column vector of constants;
- $|\mu_{0,i}| \in [0, \infty[$;
- $Z(L) = diag\{\psi(L)\}$: an $N \times N$ diagonal matrix ;
- $\psi(L) = [1 - \psi_i L]_{i=1,\dots,n}$;
- $|\psi_i| < 1$;
- $r_t = [r_{i,t}]_{i=1,\dots,N}$: the N −dimensional column vector of returns;
- $\varepsilon_t = [\varepsilon_{i,t}]_{i=1,\dots,N}$: the$N$ −dimensional column vector of residuals.

The residual vector is given by

$$\varepsilon_t = z_t \odot h_t^{\wedge 1/2} \tag{7}$$

where

- $\odot$: the Hadamard product;
- $\wedge$: the elementwise exponentiation.

$h_t = [h_{it}]_{i=1,\dots,N}$ is Σ_{t-1} measurable and the stochastic vector $z_t = [z_{it}]_{i=1,\dots,N}$ is independent and identically distributed with mean zero and positive definite covariance matrix $\rho = [\rho_{ijt}]_{i,j=1,\dots,N}$ with $\rho_{ij} = 1$ for $i = j$ .Note that $E(\varepsilon_t/\mathcal{F}_{t-1}) = 0$ and $H_t = E(\varepsilon_t \varepsilon_t'/\mathcal{F}_{t-1}) = diag(h_t^{\wedge 1/2}) \rho \, diag(h_t^{\wedge 1/2})$. h_t is the vector of conditional variances and $\rho_{i,j,t} = h_{i,j,t}/\sqrt{h_{i,t}h_{j,t}} \forall \, i,j = 1,\dots,N$ are the dynamic conditional correlations.
The multivariate FIAPARCH(1,d,1) is given by

$$B(L)\left(h_t^{\wedge\delta/2} - \omega\right) = [B(L) - \Delta(L)\Phi(L)][I_N + \Gamma_t]|\varepsilon_t|^{\wedge\delta} \tag{8}$$

where$|\varepsilon_t|$ is the vector ε_t with elements stripped of negative values.

Besides, $B(L) = diag\{\beta(L)\}$ with $\beta(L) = [1 - \beta_i L]_{i=1,\dots,N}$ and $|\beta_i| < 1$. Moreover, $\Phi(L) = diag\{\phi(L)\}$ with $\phi(L) = [1 - \phi_i L]_{i=1,\dots,N}$ and $|\phi_i| < 1$. In addition, $\omega = [\omega_i]_{i=1,\dots,N}$ with $\omega_i \in [0, \infty[$ and $\Delta(L) = diag\{d(L)\}$with $d(L) =$

$[(1 - L)^{d_i}]_{i=1,...,N}$ $\forall$ $0 \le d_i \le 1$. Finally, $\Gamma_t = diag\{\gamma \odot s_t\}$ with $\gamma = [\gamma_i]_{i=1,...,N}$ and $s_t = [s_{it}]_{i=1,...,N}$ where $s_{it} = 1$ if $\varepsilon_{it} < 0$ and 0 otherwise.

In the second stage, we estimate the conditional correlation using the transformed stock return residuals and exchange returns residuals, which are estimated by their standard deviations from the first stage. The multivariate conditional variance is specified as follows:

$$H_t = D_t R_t D_t \tag{9}$$

where $D_t = diag\left(h_{11t}^{1/2}, ..., h_{NNt}^{1/2}\right)$ denotes the conditional variance derived from the univariate AR(1)-FIAPARCH(1,d,1) model and $R_t = (1 - \theta_1 - \theta_2)R + \theta_1\psi_{t-1} + \theta_2 R_{t-1}$ is the conditional correlation matrix[3].

In addition, θ_1 and θ_2 are the non-negative parameters satisfying $(\theta_1 + \theta_2) < 1$, $R = \{\rho_{ij}\}$ is a time-invariant symmetric $N \times N$ positive definite parameter matrix with $\rho_{ii} = 1$ and ψ_{t-1} is the $N \times N$ correlation matrix of ε_τ for $\tau = t - M, t - M + 1, ..., t - 1$. The $i, j - th$ element of the matrix ψ_{t-1} is given as follows:

$$\psi_{ij,t-1} = \frac{\sum_{m=1}^{M} z_{i,t-m} z_{j,t-m}}{\sqrt{\left(\sum_{m=1}^{M} z_{i,t-m}^2\right)\left(\sum_{m=1}^{M} z_{j,t-m}^2\right)}}, \quad 1 \le i \le j \le N \tag{10}$$

where $z_{it} = \varepsilon_{it}/\sqrt{h_{iit}}$ is the transformed stock return and foreign exchange rate returns residuals by their estimated standard deviations taken from the univariate AR(1)-FIAPARCH(1,d,1) model.

The matrix ψ_{t-1} could be expressed as follows:

$$\psi_{t-1} = B_{t-1}^{-1} L_{t-1} L_{t-1}' B_{t-1}^{-1} \tag{11}$$

Where B_{t-1} is a $N \times N$ diagonal matrix with $i - th$ diagonal element given by $\left(\sum_{m=1}^{M} z_{i,t-m}^2\right)$ and $L_{t-1} = (z_{t-1}, ..., z_{t-M})$ is a $N \times N$ matrix, with $z_t = (z_{1t}, ..., z_{Nt})'$.

To ensure the positivity of ψ_{t-1} and therefore of R_t, a necessary condition is that $M \le N$. Then, R_t itself is a correlation matrix if R_{t-1} is also a correlation matrix. The correlation coefficient in a bivariate case is given as:

$$\rho_{12,t} = (1 - \theta_1 - \theta_2)\rho_{12} + \theta_2\rho_{12,t} + \theta_1 \frac{\sum_{m=1}^{M} z_{1,t-m} z_{2,t-m}}{\sqrt{(\sum_{m=1}^{M} z_{1,t-m}^2)(\sum_{m=1}^{M} z_{2,t-m}^2)}} \tag{12}$$

3Engle (2002) derives a different form of DCC model. The evolution of the correlation in DCC is given by: $Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha z_{t-1} + \beta Q_{t-1}$, where $Q = (q_{ijt})$ is the $N \times N$ time-varying covariance matrix of z_t, $\bar{Q} = E[z_t z_t']$ denotes the $n \times n$ unconditional variance matrix of z_t, while α and β are nonnegative parameters satisfying $(\alpha + \beta) < 1$. Since Q_t does not generally have units on the diagonal, the conditional correlation matrix R_t is derived by scaling Q_t as follows: $R_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2}$.

2.3 A-DCC-EGARCH Model

To investigate the dynamics of the correlations between European exchange rate expressed in US dollar (USD) and three stock prices namely NIKKEI225, SSE and MSCI, we use the asymmetric generalized dynamic conditional correlation (AG-DCC) model developed by Cappiello et al. (2006). This approach generalizes the DCC model of Engle (2002) by introducing two modifications: asset-specific correlation evolution parameters and conditional asymmetries in correlation dynamics. In this paper, we adopt the following three step approach (see also Kenourgios et al., 2011; Toyoshima et al., 2012; Samitas and Tsakalos, 2013; Toyoshima and Hamori, 2013). In the first step, we estimate the conditional variances of exchange rate returns and stock market returns using an autoregressive- asymmetric exponential generalized autoregressive conditional heteroscedasticity $(AR(m) - EGARCH(p, q))$ model[4]. For a more detailed analysis, we use the following equations:

$$r_t = \mu_0 + \sum_{i=1}^{m} \mu_i r_{t-i} + \varepsilon_t \tag{13}$$

$$ln(h_t) = \omega + \sum_{i=1}^{q} [\alpha_i |z_{t-i}| + \gamma_i z_{t-i}] + \sum_{i=1}^{p} \beta_i ln(h_{t-i}) \tag{14}$$

where r_t indicates exchange rate and stock market returns, ε_t is the error term, h_t is the conditional volatility, and $z_t = \varepsilon_t / \sqrt{h_t}$ is the standardized residual.

The EGARCH model has several advantages over the pure GARCH specification. First, since $ln(h_t)$ is modelled, then even if the parameters are negative, h_t will be positive. Thus, there is no need to artificially impose non-negativity constraints on the model parameters. Second, asymmetries are allowed for under the EGARCH formulation, since if the relationship between volatility and returns is negative, γ_i will be negative. Note that a negative value of γ_i means that negative residuals tend to produce higher variances in the immediate future.

Furthermore, we assume that the random variable z_t has a student distribution (see Bollerslev, 1987) with $v > 2$ degrees of freedom with a density given by:

$$D(z_t, v) = \frac{\Gamma(v + \frac{1}{2})}{\Gamma(\frac{v}{2})\sqrt{\pi(v-2)}} \left(1 + \frac{z_t^2}{v-2}\right)^{\frac{1}{2} - v} \tag{15}$$

where $\Gamma(v)$ is the gamma function and v is the parameter that describes the thickness of the distribution tails. The Student distribution is symmetric around zero and, for $v > 4$, the conditional kurtosis equals $3(v - 2)/(v - 4)$, which exceeds the normal value of three. For large values of v, its density converges to that of the standard normal.

The log form of the EGARCH(p,q) model ensures the positivity of the conditional variance, without the need to constrain the parameters of the model. The term z_{t-i} indicates the asymmetric effect of positive and negative shocks. If $\gamma_i > 0$, then $z_{t-i} = \varepsilon_{t-i}/\sigma_{t-i}$ is

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[4]See Nelson (1991).

positive. The term $\sum_{i=1}^{p} \beta_i$ measures the persistence of shocks to the conditional variance. The conditional mean equation (Eq. 13) is specified as an autoregressive process of order m. The optimal lag length m for each exchange return series is given by the Schwartz-Bayesian Information Criterion (SBIC). Eq. (14) represents the conditional variance and is specified as and EGARCH(p,q) process. The optimal lag lengths p and q are determined by employing the SBIC criterion. From Eq. 14, we first obtain the conditional volatilities and then recover the conditional correlations. The conditional covariance matrix is then defined as follows:

$$H_t = D_t R_t D_t \tag{16}$$

where the diagonal matrix D_t is the conditional standard deviation obtained from Eq. (14). The matrix of the standardized residuals Z_t is used to estimate the parameters of the asymmetric dynamic conditional correlation (A-DCC) model developed by Cappiello et al. (2006). The AG-DCC model is given as

$$Q_t = (\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G) + A'Z_{t-1}Z'_{t-1}A + B'Q_{t-1}B + G'\eta_{t-1}\eta'_{t-1}G \tag{17}$$

where $\bar{Q}$ and $\bar{N} = E(\eta_t \eta'_t)$ are the unconditional correlation matrices of Z_t and η_t. $\eta_t = I[Z_t < 0] \circ Z_t$. $I[.]$ is an indicator function such that $I = 1$ if $Z_t < 0$ and $I = 0$ if $Z_t \geq 0$, while $" \circ "$ is the Hadamard product.

The A-DCC(1,1) model is identified as a special case of the AG-DCC(1,1) model if the matrices A, B and G are replaced by the scalars a_1, b_1 and g_1. Cappiello et al. (2006) show that Q_t is positive definite with a probability of one if $(\bar{Q} - A'\bar{Q}A - B'\bar{Q}B - G'\bar{N}G)$ is positive definite. The next step consists in computing the correlation matrix R_t from the following equation:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \tag{18}$$

where $Q_t^* = \sqrt{q_{ii,t}}$ is a diagonal matrix with a square root of the ith diagonal element of Q_t on its ith diagonal position.

3   Data and Preliminary Analyses

The data comprises daily American exchange rate expressed in euro (EUR) of the European foreign currencies and daily stock prices namely, NIKKEI225, SSE and MSCI. All data are sourced from the Board of Governors of the Federal Reserve System and (http// www.econstats.com). The sample covers a period from January 01, 2000 until December 10, 2013, leading to a sample size of 3639 observations. For each currency and stock prices, the continuously compounded return is computed as: $r_t = 100 * \ln(\frac{p_t}{p_{t-1}})$ for t = 1, 2, …

T, where p_t is the price on day t.

Summary statistics for the exchange rate and stock market returns are displayed in Table 1 (Panel A). From these tables, SSE is the most volatile, as measured by the standard deviation of 1.5456%, while USDEUR is the least volatile with a standard deviation of 0.6366%. Besides, we observe that NIKKEI225 has the highest level of excess kurtosis,

indicating that extreme changes tend to occur more frequently for this stock price. In addition, all stock index and exchange rate returns exhibit high values of excess kurtosis. Furthermore, the Jarque-Bera statistic rejects normality at the 1% level for all stock index and exchange rate. Moreover, all exchange rate and stock market return series are stationary, I(0), and thus suitable for long memory tests. Finally, they exhibit volatility clustering, revealing the presence of heteroskedasticity and strong ARCH effects.

In order to detect long-memory process in the data, we use the log-periodogram regression (GPH) test of Geweke and Porter-Hudak (1983) on two proxies of volatility, namely squared returns and absolute returns. The test results are displayed in Table 1 (Panel D). Based on these tests results, we reject the null hypothesis of no long-memory for absolute and squared returns at 1% significance level. Subsequently, all volatilities proxies seem to be governed by a fractionally integrated process. Thus, FIAPARCH seem to be an appropriate specification to capture volatility clustering, long-range memory characteristics and asymmetry.

Fig. 1 illustrates the evolution of exchange rate and stock index during the period from January 1, 2000 until December 10, 2013. The figure shows significant variations in the levels during the turmoil, especially at the time of Lehman Brothers failure (September 15, 2008). Specifically, when the global financial crisis triggered, there was a decline for all currencies. Fig. 2 plots the evolution of currencies returns and stock market returns over time. The figure shows that all exchange rate and stock index trembled since 2008 with different intensity during the global financial and European sovereign debt crises. Moreover, the plot shows a clustering of larger return volatility around and after 2008. This means that foreign exchange and stock markets are characterized by volatility clustering, i.e., large (small) volatility tends to be followed by large (small) volatility, revealing the presence of heteroskedasticity. This market phenomenon has been widely recognized and successfully captured by ARCH/GARCH family models to adequately describe exchange rate and stock market returns dynamics.

Table 1: Summary statistics and long memory test's results.

	USD/EUR	NIKKEI225	SSE	MSCI
Panel A: descriptive statistics				
Mean	-8.50E-03	-0.0053	0.0135	-1.77E-05
Maximum	3.0031	13.235	9.4008	6.5246
Minimum	-4.6208	-12.111	-9.2562	-9.936
Std. Deviation	0.6366	1.5304	1.5456	1.4641
Skewness	-0.0781*	-0.4348***	-0.0887**	-0.241***
	(0.0542)	(0.0000)	(0.0287)	(0.0000)
ExcessKurtosis	2.2977***	6.8355***	4.7723***	3.0688***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Jarque-Bera	804.2***	7199.2***	3458.0***	1463.2***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Panel B: Serial correlation and LM-ARCH tests				
$LB(20)$	21.8227	14.4001	44.7177***	72.6072***
	(0.3502)	(0.8096)	(0.0012)	(0.0000)
$LB^2(20)$	662.323***	3792.4***	695.483***	1433.72***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ARCH 1-10	23.031***	141.66***	25.233***	44.144***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Panel C: Unit Root tests				
ADF test statistic	-34.9843***	-36.819***	-33.7277***	-33.1275***
	-1.9409	-1.9409	-1.9409	-1.9409
Panel D: long memory tests (GPH test−d estimates)				
Squared returns				
$m = T^{0.5}$	0.4106	0.2687	0.4593	0.5946
	[0.0968]	[0.0573]	[0.0813]	[0.0900]
$m = T^{0.6}$	0.5947	0.4649	0.369	0.3955
	[0.0732]	[0.0498]	[0.0620]	[0.0580]
Absolute returns				
$m = T^{0.5}$	0.4825	0.3403	0.4781	0.5623
	[0.0747]	[0.0812]	[0.0838]	[0.1050]
$m = T^{0.6}$	0.5804	0.4487	0.37002	0.4381
	[0.0698]	[0.0570]	[0.0568]	[0.0697]

Notes:Exchange rate and Stock market returns are in daily frequency. r^2 and $|r|$ are squared log return and absolute log return, respectively. m denotes the bandwith for the Geweke and Porter-Hudak's (1983) test. Observations for all series in the whole sample period are 3639. The numbers in brackets are t-statistics and numbers in parentheses are p-values. ***, **, and * denote statistical significance at 1%, 5% and 10% levels, respectively. $LB(20)$ and $LB^2(20)$ are the 20th order Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, respectively.
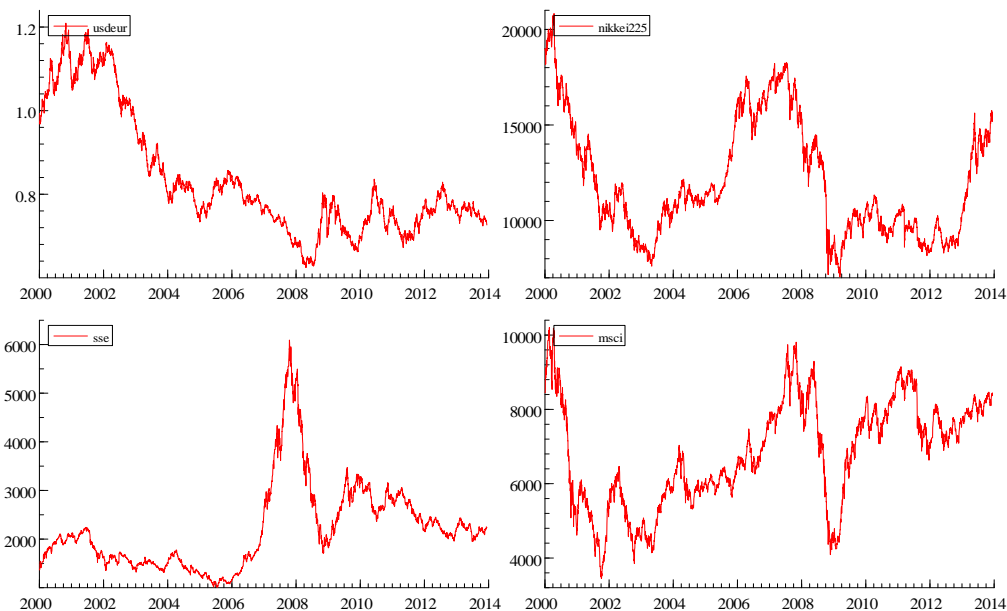
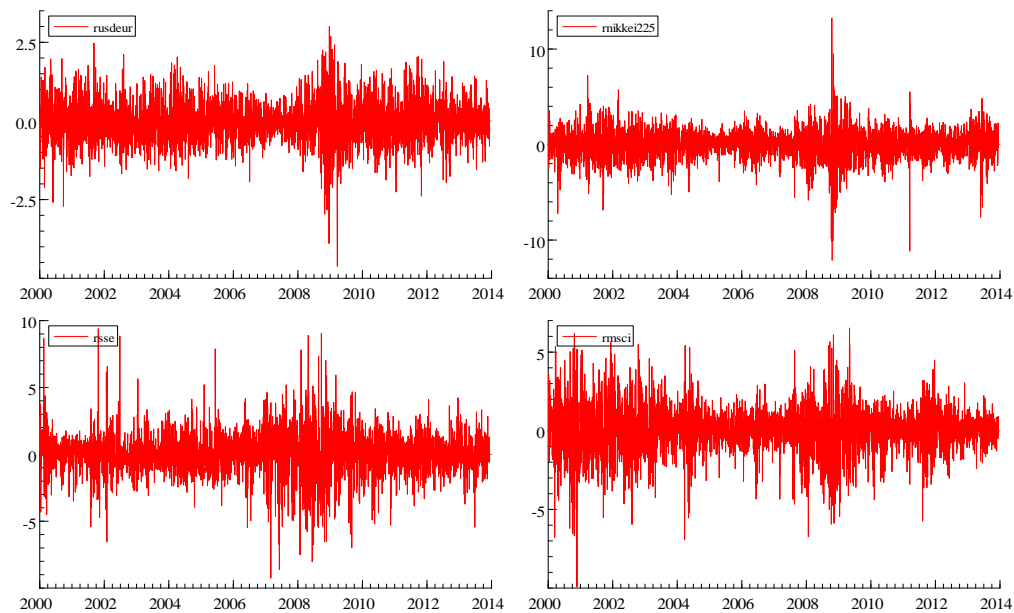Figure1: Exchange rate and stock index behavior over time

Figure2: Exchange rate and stock market returns behavior over time.

4   Empirical Results

4.1 Tests for Sign and Size Bias

Engle and Ng (1993) propose a set of tests for asymmetry in volatility, known as sign and size bias tests. The Engle and Ng tests should thus be used to determine whether an asymmetric model is required for a given series, or whether the symmetric GARCH model can be deemed adequate. In practice, the Engle-Ng tests are usually applied to the residuals of a GARCH fit to the returns data.

Define S_{t-1}^- as an indicator dummy variable such as:

$$S_{t-1}^- = \begin{cases} 1 \ if \ \hat{z}_{t-1} < 0 \\ 0 \quad \text{otherwise} \end{cases} \tag{19}$$

The test for sign bias is based on the significance or otherwise of ϕ_1 in the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \nu_t \tag{20}$$

Where ν_t is an independent and identically distributed error term. If positive and negative shocks to $\hat{z}_{t-1}$ impact differently upon the conditional variance, then ϕ_1 will be statistically significant.
It could also be the case that the magnitude or size of the shock will affect whether the response of volatility to shocks is symmetric or not. In this case, a negative size bias test would be conducted, based on a regression where S_{t-1}^- is used as a slope dummy variable. Negative size bias is argued to be present if ϕ_1 is statistically significant in the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- z_{t-1} + \nu_t \tag{21}$$

Finally, we define $S_{t-1}^+ = 1 - S_{t-1}^-$, so that S_{t-1}^+ picks out the observations with positive innovations. Engle and Ng (1993) propose a joint test for sign and size bias based on the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- z_{t-1} + \phi_3 S_{t-1}^+ z_{t-1} + \nu_t \tag{22}$$

Significance of ϕ_1 indicates the presence of sign bias, where positive and negative shocks have differing impacts upon future volatility, compared with the symmetric response required by the standard GARCH formulation. However, the significance of ϕ_2 or ϕ_3 would suggest the presence of size bias, where not only the sign but the magnitude of the shock is important. A joint test statistic is formulated in the standard fashion by calculating TR^2 from regression (22), which will asymptotically follow a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects.

Table 2: Tests for sign and size bias for exchange rate and stock marketreturn series.

Variables	USD/EUR			NIKKEI225			SSE			MSCI		
	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif
ϕ_0	1.2461***	0.0561	0.0000	1.0623***	0.0734	0.0000	0.9628	0.0799	0.0000	1.0703***	0.0721	0.0000
ϕ_1	-0.240***	0.0845	0.0044	0.0468	0.0944	0.6197	0.0572	0.1065	0.5911	0.0786	0.0940	0.4033
ϕ_2	0.1511**	0.0624	0.0154	0.0067	0.0579	0.9072	-0.0614	0.0705	0.3837	0.0352	0.0584	0.5467
ϕ_3	-0.195***	0.0567	0.0005	-0.235***	0.0756	0.0018	-0.0352	0.0795	0.6576	-0.2810***	0.0748	0.0001
$\chi^2(3)$	33.041***	_	0.0000	23.0797***	_	0.0000	37.317*		0.0919	31.916***	_	0.0000

Note: The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively.

Table 2 reports the results of Engle-Ng tests. First, the individual regression results show that the residuals of the symmetric GARCH model for the NIKKEI225 and MSCI series do not suffer from sign bias and/or negative size bias, but they do exhibit positive size bias. Second, for the SSE series, the individual regression results show that the residuals of the symmetric GARCH model do not suffer from sign bias. Third, the individual regression results show that the residuals of the symmetric GARCH model for the USDEUR series exhibit sign bias, negative size bias and/or positive size bias. Finally, the $\chi^2(3)$ joint test statistics have *p*-values of 0.0000 and 0.0919, respectively, demonstrating a very rejection of the null of no asymmetries. The results overall would thus suggest motivation for estimating an asymmetric volatility model for these particular series.

4.2 The univariate FIAPARCH estimates

In order to take into account the serial correlation and the GARCH effects observed in our time series data, and to detect the potential long range dependence in volatility, we estimate the student[5]-t-AR(0)-FIAPARCH(1,d,1)[6] model defined by Eq. (1) and Eq. (5). Table 3 reports the estimation results of the univariate FIAPARCH(1,d,1) model for each stock prices exchange rate returns series of our sample.

The estimates of the constants in the mean are statistically significant for all the series except for NIKKEI225 stock price. Besides, the constants in the variance are significant except for USDEUR and MSCI. In addition, for all currencies, the estimates of the leverage term (γ) are statistically significant, except for the USDEUR indicating an asymmetric

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[5]The z_t random variable is assumed to follow a student distribution (see Bollerslev, 1987) with $v > 2$ degrees of freedom and with a density given by:

$$D(z_t, v) = \frac{\Gamma(v + \frac{1}{2})}{\Gamma(\frac{v}{2})\sqrt{\pi(v-2)}}(1 + \frac{z_t^2}{v-2})^{\frac{1}{2}-v}$$

where $\Gamma(v)$ is the gamma function and v is the parameter that describes the thickness of the distribution tails. The Student distribution is symmetric around zero and, for $v > 4$, the conditional kurtosis equals $3(v-2)/(v-4)$, which exceeds the normal value of three. For large values of v, its density converges to that of the standard normal.

For a Student-t distribution, the log-likelihood is given as: $L_{Student} = T\left\{log\Gamma\left(\frac{v+1}{2}\right) - log\Gamma\left(\frac{v}{2}\right) - \frac{1}{2}log[\pi(v-2)]\right\} - \frac{1}{2}\sum_{t=1}^{T}\left[log(h_t) + (1+v)log\left(1 + \frac{z_t^2}{v-2}\right)\right]$

where T is the number of observations, v is the degrees of freedom, $2 < v \leq \infty$ and $\Gamma(.)$ is the gamma function.

[6] The lag orders $(1, d, 1)$ and $(0,0)$ for FIAPARCH and ARMA models, respectively, are selected by Akaike (AIC) and Schwarz (SIC) information criteria. The results are available from the author upon request.

response of volatilities to positive and negative shocks. This finding confirms the assumption that there is negative correlation between returns and volatility.

Moreover, the estimates of the power term (δ) are highly significant for all currencies and ranging from 1.4198 to 1.9252. Conrad et al. (2011) show that when the series are very likely to follow a non-normal error distribution, the superiority of a squared term $(\delta = 2)$ is lost and other power transformations may be more appropriate. Thus, these estimates support the selection of FIAPARCH model for modeling conditional variance of exchange rate returns and stock market returns. Besides, all currencies display highly significant differencing fractional parameters (d), indicating a high degree of persistence behavior. This implies that the impact of shocks on the conditional volatility of exchange rates' returns and stock market consistently exhibits a hyperbolic rate of decay. In all cases, the estimated degrees of freedom parameter (v) is highly significant and leads to an estimate of the Kurtosis which is equal to $3(v - 2)/(v - 4)$ and is also different from three.

Table 3: Univariate FIAPARCH(1,d,1) models (MLE).

	USDEUR		NIKKEI225		SSE		MSCI	
	Coeff	t-prob	Coeff	t-prob	Coeff	t-prob	Coeff	t-prob
Estimate								
c	-0.0182**	0.0480	0.0269	0.1760	0.0291*	0.0946	0.0483***	0.0046
ω	0.0049	0.2689	0.1353***	0.0014	0.2771***	0.0080	0.0450	0.2037
d	0.9225***	0.0000	0.4102***	0.0000	0.3146***	0.0000	0.3132***	0.0000
ϕ	-0.0223	0.6737	0.1116**	0.0368	-0.1097	0.3816	0.1731***	0.0091
β	0.9461***	0.0000	0.4919***	0.0000	0.1428	0.3486	0.4571***	0.0000
γ	0.0136	0.8531	0.4465***	0.0010	0.3323***	0.0000	0.5574***	0.0032
δ	1.4198***	0.0037	1.4582***	0.0000	1.9252***	0.0000	1.6832***	0.0000
v	8.8139***	0.0000	8.2601***	0.0000	3.6846***	0.0000	6.1827***	0.0000
Diagnostic								
$LB(20)$	12.9805	0.8782	11.7653	0.9239	53.5749***	0.0000	45.0142***	0.0010
$LB^2(20)$	20.5600	0.3021	31.2876**	0.0266	10.6958	0.9068	29.9101	0.3359

Notes: For each of the five exchange rates, Table 2 reports the Maximum Likelihood Estimates (MLE) for the student-t-FIAPARCH(1,d,1) model. $LB(20)$ and $LB^2(20)$ indicate the Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, respectively. $v$denotes the the t-student degrees of freedom.parameter ***, ** and * denote statistical significance at 1%, 5% and 10% levels, respectively.

In addition, all the ARCH parameters (ϕ) satisfy the set of conditions which guarantee the positivity of the conditional variance, except for the two series (USDEUR and SSE). Moreover, according to the values of the Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, there is no statistically significant evidence, at the 1% level, of misspecification in almost all cases.

Numerous studies have documented the persistence of volatility in stock and exchange rate returns (see Ding et al., 1993; Ding and Granger, 1996, among others). The majority of these studies have shown that the volatility process is well approximated by an IGARCH process. Nevertheless, from the FIAPARCH estimates reported in Table 3, it appears that the long-run dynamics are better modeled by the fractional differencing parameter.

To test for the persistence of the conditional heteroskedasticity models, we examine the Likelihood Ratio (LR) statistics for the linear constraints $d = 0$ (APARCH(1,1) model) and $d \neq 0$ (FIAPARCH(1,d,1) model). We construct a series of LR tests in which the

restricted case is the APARCH(1,1) model $(d = 0)$ of Ding et al. (1993). Let l_0 be the log-likelihood value under the null hypothesis that the true model is APARCH(1,1) and l the log-likelihood value under the alternative that the true model is FIAPARCH(1,d,1). Then, the LR test, $2(l - l_0)$, has a chi-squared distribution with 1 degree of freedom when the null hypothesis is true.

For reasons of brevity, we omit the table with the test results, which are available from the author upon request. In summary, the LR tests provide a clear rejection of the APARCH(1,1) model against the FIAPARCH(1,d,1) one for all currencies. Thus, purely from the perspective of searching for a model that best describes the volatility in the exchange rate and stock price series, the FIAPARCH(1,d,1) model appears to be the most satisfactory representation. This finding is important since the time series behavior of volatility could affect asset prices through the risk premium (see Christensen and Nielsen, 2007; Christensen et al., 2010; Conrad et al., 2011).

With the aim of checking for the robustness of the LR testing results discussed above, we apply the Akaike (AIC), Schwarz (SIC), Shibata (SHIC) or Hannan-Quinn (HQIC) information criteria to rank the ARCH type models. According to these criteria, the optimal specification (i.e., APARCH or FIAPARCH) for all currencies is the FIAPARCH one. The two common values of the power term (δ) imposed throughout much of the GARCH literature are $\delta = 2$ (Bollerslev's model) and $\delta = 1$ (the Taylor/Schwert specification). According to Brooks et al. (2000), the invalid imposition of a particular value for the power term may lead to sub-optimal modeling and forecasting performance. For that reason, we test whether the estimated power terms are significantly different from unity or two using Wald tests (results not reported).

We find that all four estimated power coefficients are significantly different from unity. Furthermore, each of the power terms is significantly different from two. Hence, on the basis of these findings, support is found for the (asymmetric) power fractionally integrated model, which allows an optimal power transformation term to be estimated. The evidence obtained from the Wald tests is reinforced by the model ranking provided by the four model selection criteria (values not reported). This is a noteworthy result since He and Teräsvirta (1999) emphasized that if the standard Bollerlsev type of model is augmented by the 'heteroskedasticity' parameter, the estimates of the ARCH and GARCH coefficients almost certainly change. More importantly, Karanasos and Schurer (2008) show that, in the univariate GARCH-in-mean level formulation, the significance of the in-mean effect is sensitive to the choice of the power term.

4.3 The Bivariate FIAPARCH(1,d,1)-DCC Estimates

The analysis above suggests that the FIAPARCH specification describes the conditional variances of the exchange rate and three stock prices well. Nevertheless, exchange rate market and stock market volatilities move together across assets and markets. According to Bauwens and Laurent (2005), Bauwens et al. (2006) and Silvennoinen and Terasvirta (2007), among others, recognizing this feature through a multivariate modeling structure could lead to obvious gains in efficiency compared to working with separate univariate specifications. Therefore, the multivariate FIAPARCH model seems to be essential for enhancing our understanding of the relationships between the (co)volatilities of economic and financial time series.

In this section, within the framework of the multivariate DCC model, we analyze the

dynamic adjustments of the variances for the three stock prices and exchange rate. Overall, we estimate three bivariate specifications for our analysis. Table 4 (Panels A and B) reports the estimation results of the bivariate student-t-FIAPARCH(1,d,1)-DCC model. The ARCH and GARCH parameters (a and b) of the DCC(1,1) model capture, respectively, the effects of standardized lagged shocks and the lagged dynamic conditional correlations effects on current dynamic conditional correlation. They are statistically significant at the 1% and 5% levels, indicating the existence of time-varying correlations. Moreover, they are non-negative, justifying the appropriateness of the FIAPARCH model. When $a = 0$ and $b = 0$, we obtain the Bollerslev's (1990) Constant Conditional Correlation (CCC) model. As shown in Table 4, the estimated coefficients a and b are significantly positive and satisfy the inequality $a + b < 1$ in each of the pairs of exchange rate and stock prices. Besides, the t-student degrees of freedom parameter (v) is highly significant, supporting the choice of this distribution.

The statistical significance of the DCC parameters (a and b) reveals a considerable time-varying comovement and thus a high persistence of the conditional correlation. The sum of these parameters is close to unity and range between 0.9825 (USDEUR-NIKKEI225) and 0.9995 (USDEUR-MSCI). This implies that the volatility displays a highly persistent fashion. Since $a + b < 1$, the dynamic correlations revolve around a constant level and the dynamic process appears to be mean reverting. The multivariate FIAPARCH-DCC model is so important to consider in our analysis since it has some key advantages. First, it captures the long range dependence property. Second, it allows obtaining all possible pair-wise conditional correlation coefficients for the exchange rate returns and stock prices in the sample. Third, it's possible to investigate their behavior during periods of particular interest, such as periods of the global financial and European sovereign debt crises. Fourth, the model allows looking at possible financial contagion effects between international foreign exchange and stock markets.

Finally, it is crucial to check whether the selected exchange rate and stock price series display evidence of multivariate Long Memory ARCH effects and to test ability of the Multivariate FIAPARCH specification to capture the volatility linkages among currencies. Kroner and Ng (1998) have confirmed the fact that only few diagnostic tests are kept to the multivariate GARCH-class models compared to the diverse diagnostic tests devoted to univariate counterparts. Furthermore, Bauwens et al. (2006) have noted that the existing literature on multivariate diagnostics is sparse compared to the univariate case. In our study, we refer to the most broadly used diagnostic tests, namely the Hosking's and Li and McLeod's Multivariate Portmanteau statistics on both standardized and squared standardized residuals. According to Hosking (1980), Li and McLeod (1981) and McLeod and Li (1983) autocorrelation test results reported in Table 4 (Panel B), the multivariate diagnostic tests allow accepting the null hypothesis of no serial correlation on both standardized and squared standardized residuals and thus there is no evidence of statistical misspecification.
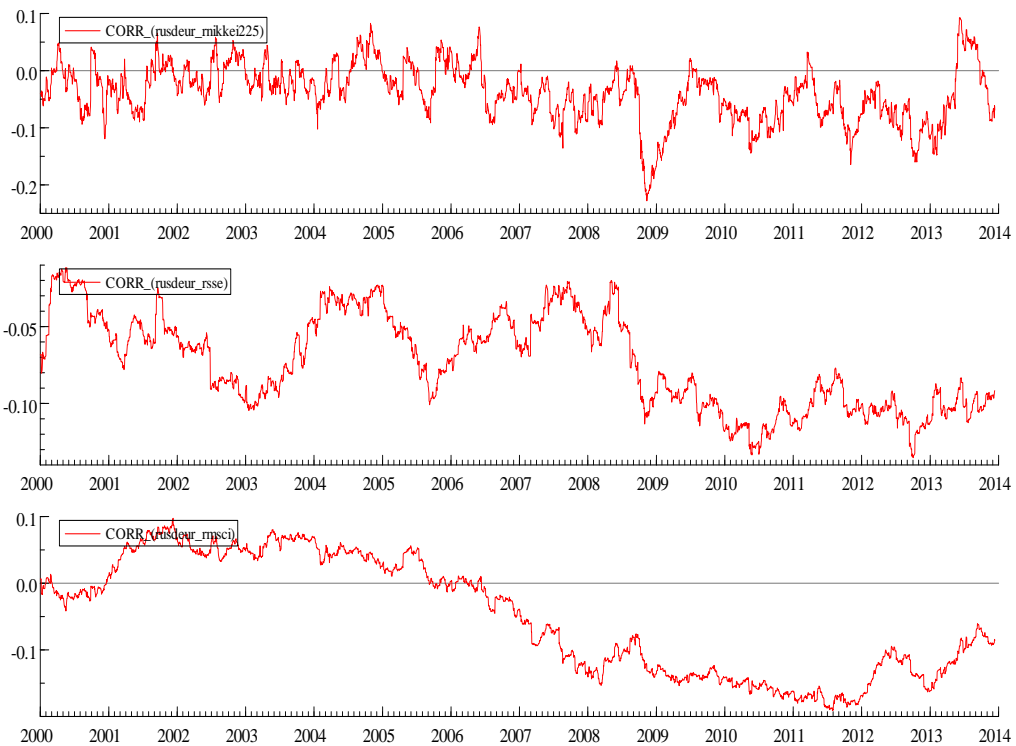
Figure 3: The DCC behavior over time

In order to further examine whether the conditional correlations changed over time, we use the LM Test for Constant Correlation of Tse (2000) and the Engle and Sheppard (2001) test for dynamic correlation (results are not reported and are available from the author upon request). Tests results show a statistically significant rejection of the constant conditional correlation (CCC) hypothesis for all pair-wise conditional correlations among currencies. Figure 3 illustrates the evolution of the estimated dynamic conditional correlations dynamics among foreign exchange market and stock prices. Compared to the pre-crises period, the estimated DCCs show a decline during the post-crises period. Such evidence is in contrast with the findings of previous research on foreign exchange and stock markets, which show increases in correlations during periods of financial turmoil (see Kenourgios et al., 2011; Dimitriou et al., 2013; Dimitriou and Kenourgios, 2013).Nevertheless, the different path of the estimated DCCs displays fluctuations for all pairs of exchange rate and stock prices across the phases of the global financial and European sovereign debt crises, suggesting that the assumption of constant correlation is not appropriate. The above findings motivate a more extensive analysis of DCCs, in order to capture contagion dynamics during different phases of the two crises.

Table 4: Estimation results from the bivariate FIAPARCH(1,d,1)-DCC model.

	USDEUR-NIKKEI225		USDEUR-SSE		USDEUR-MSCI	
	coefficient	t-prob	coefficient	t-prob	coefficient	t-prob
Panel A: Estimates of Multivariate DCC						
a	0.0088**	0.0449	0.0022	0.4961	0.0028***	0.0071
b	0.9737***	0.0000	0.9944***	0.0000	0.9967***	0.0000
v	9.9540***	0.0000	6.9175***	0.0000	9.0447***	0.0000
Panel B : Diagnostic tests						
$Hosking(20)$	63.0281	0.9187	123.299***	0.0013	108.048**	0.0200
$Hosking^2(20)$	78.8312	0.4523	58.3638	0.9528	92.1543	0.1305
$Li-McLeod(20)$	63.0694	0.9181	123.181***	0.0013	108.002**	0.0202
$Li-McLeod^2(20)$	78.8311	0.4523	58.4263	0.9522	92.1043	0.1313

Notes:The superscripts ***, ** and * denote the statistical significance at 1%, 5% and 10% levels, respectively. v indicates the student's distribution's degrees of freedom. $Hosking(20)$ and $Hosking^2(20)$ denote the Hosking's Multivariate Portmanteau Statistics on both standardized and squared standardized Residuals. $Li-McLeod(20)$ and $Li-McLeod^2(20)$ indicate the Li and McLeod's Multivariate Portmanteau Statistics on both Standardized and squared standardized Residuals.

4.4 AR-EGARCH Specification

The first step of this specification is to estimate the univariate $AR(m)-EGARCH(p,q)$ models for each exchange rate and stock market return series (see Table 5). This paper considers the asymmetric effect, while Tamakoshi and Hamori (2014) did not. The AR(0)-EGARCH(1,1) model is choosen for all exchange rate and stock market return series.The estimated parameters of the EGARCH(1,1) model are statistically significant at the 1% significance level or better for the four variables, except the γ parameter for the USDEUR variable.Table 5 also reports the estimates of the parameter β, which measures the degree of volatility persistence. We find that β for European exchange rate returns expressed in US dollar, and major stock market returns are 0.9951, 0.9743, 0.9865 and 0.9910, respectively. From these estimates, we could infer that the persistence in shocks to volatility is relatively large.

In addition, Table 4 depicts the diagnostics of the empirical findings of the AR(0)-EGARCH(1,1) model. $LB-Q(20)$ and $LB-Q^2(20)$ are the Ljung-Box test statistics for the null hypothesis that there is no serial correlation up to order 20 for standardized and squared standardized residuals, respectively. The null hypothesis of no autocorrelation up to order 20 for squared standardized residuals is also accepted at the 1% level of significance.

Since our analysis focused on the dynamics of the correlations among the exchange rate and stock market returns, the well-fitted variance equations described above led us to conclude that our AR-EGARCH models fit the data rationally well.

4.5 Multivariate Asymmetric DCC Results

The second step of our analysis is to estimate the multivariate A-DCC model developed by Cappiello et al. (2006). The estimation results of the DCC and A-DCC models are reported in Table 6.We use this methodology to test the correlation among the selected three stock market returns and exchange rate.Generally, we find that the A-DCC model seems to be specified reasonably well.Indeed, the estimates of the parameter of standardized residuals (a_1) and of innovations in the dynamics of the conditional correlation matrix (b_1) are significant at the 1% level or better.Most remarkably, the estimate of the parameter of the asymmetric term (g_1) is significant at the 10% level or better, thus providing evidence of an asymmetric response in correlations. In other words, the conditional correlation among the currencies exhibits higher dependency when it is driven by negative innovations to changes than it is by positive innovations. This result is rather interesting because it suggests that the reasons for the identified asymmetric correlation differ from the theoretical explanation of the "currency portfolio rebalancing" hypothesis, which argues that exchange rates tend to display a higher degree of co-movement during periods of their depreciation than during periods of their appreciation against the USD.

Table 5: AR(0)-EGARCH(1,1) estimation results.

	USDEUR				NIKKEI225		
	Coefficient	Std.Error	p-value		Coefficient	Std.Error	p-value
μ_0	-0.0215**	0.0088	0.0156		0.0261	0.0172	0.1292
ω	-0.054***	0.0069	0.0000		-0.096***	0.0111	0.0000
α	0.0651***	0.0081	0.0000		0.1465***	0.0154	0.0000
β	0.9951***	0.0017	0.0000		0.9743***	0.0049	0.0000
γ	0.007	0.0058	0.2291		-0.083***	0.0119	0.0000
Student-t parameter (v)	8.4739***	1.1829	0.0000		8.2359***	1.0793	0.0000
Student-t parameter (v)	-3287.36	_	_		-6182.78	_	_
$LB - Q(20)$	14.2471	_	0.8177		10.3289	_	0.9618
$LB - Q^2(20)$	27.5035*	_	0.0700		27.8325*	_	0.0646

Notes : $r_t = \mu_0 + \varepsilon_t$ and $ln(h_t) = \omega + \alpha|z_{t-1}| + \gamma z_{t-1} + \beta ln(h_{t-1})$, where r_t represents exchange rate returns and stock prices, ε_t is the error term, h_t is the conditional volatility and $z_t = \varepsilon_t/\sigma_t$ is the standardized residual. $LB – Q(20)$ and $LB – Q^2(20)$ are the Ljung-Box statistics with 20 lags for the standardized and squared standardized residuals, respectively. The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively
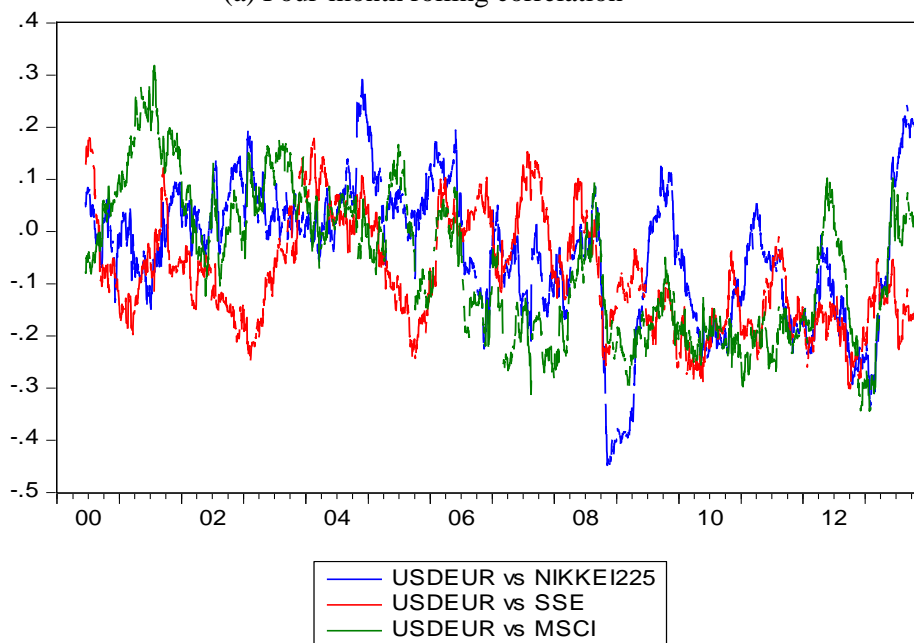
Table 5 (continued): AR(0)-EGARCH(1,1) estimation results.

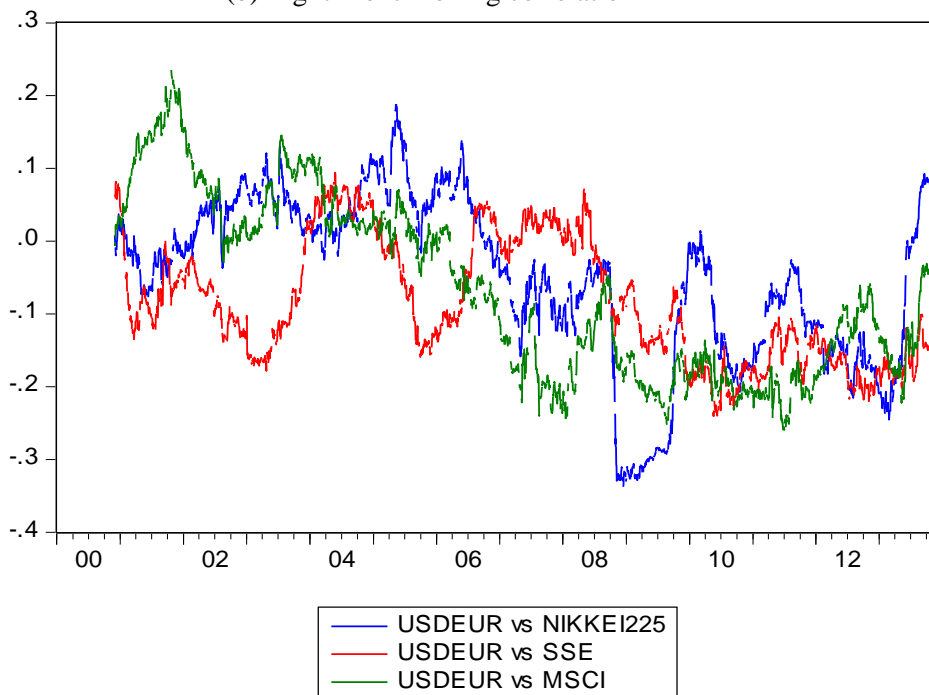|	SSE				MSCI		
	Coefficient	Std.Error	p-value		Coefficient	Std.Error	p-value
μ_0	0.0344**	0.0158	0.0293		0.0518***	0.0167	0.0019
ω	-0.091***	0.0139	0.0000		-0.079***	0.0103	0.0000
α	0.1508***	0.0249	0.0000		0.1120***	0.0146	0.0000
β	0.9865***	0.0051	0.0000		0.9910***	0.0026	0.0000
γ	-0.034***	0.0112	0.0021		-0.057***	0.0089	0.0000
Student-t parameter (v)	3.6516***	0.2692	0.0000		5.8489***	0.6016	0.0000
Student-t parameter (v)	-6171.71	_	_		-5952.15	_	_
$LB - Q(20)$	51.7303***	_	0.0001		43.1426***	_	0.0019
$LB - Q^2(20)$	10.2005	_	0.9251		35.7654***	_	0.0075

Notes : $r_t = \mu_0 + \varepsilon_t$ and $ln(h_t) = \omega + \alpha|z_{t-1}| + \gamma z_{t-1} + \beta ln(h_{t-1})$, where r_t represents exchange rate returns and stock prices, ε_t is the error term, h_t is the conditional volatility and $z_t = \varepsilon_t/\sigma_t$ is the standardized residual. $LB - Q(20)$ and $LB - Q^2(20)$ are the Ljung-Box statistics with 20 lags for the standardized and squared standardized residuals, respectively. The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively

In Fig. 4, we plot the rolling correlations between each pair of exchange rate and stock prices with time spans of four months, eight months, one year, two years and four years, respectively. Interestingly, we find more fluctuations of the rolling correlations in downward directions between each pair, particularly after 2007, regardless of the selected time spans.
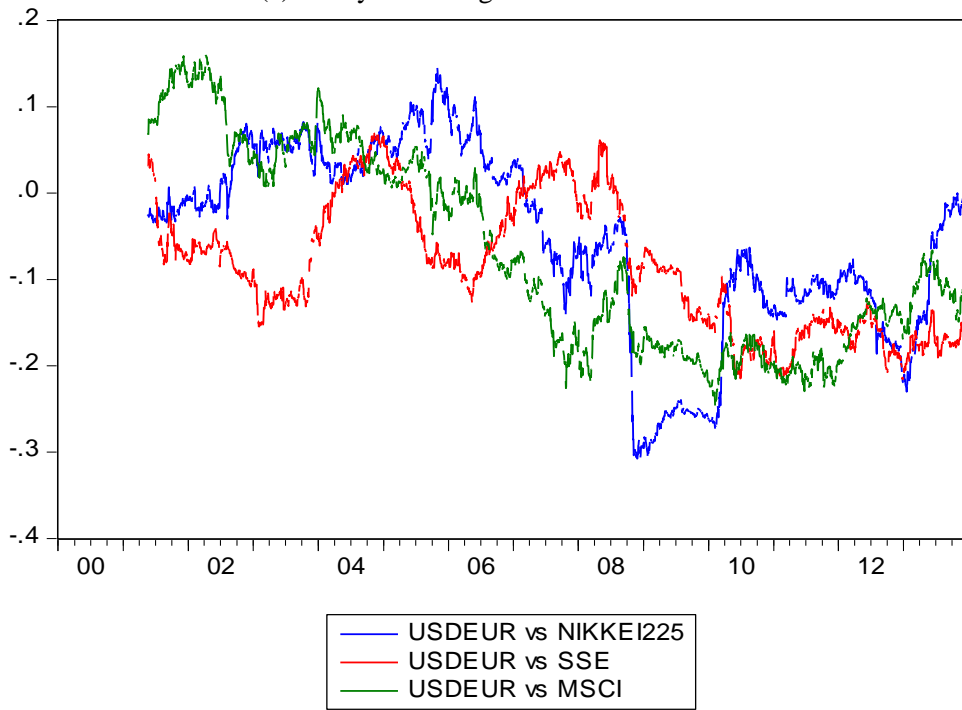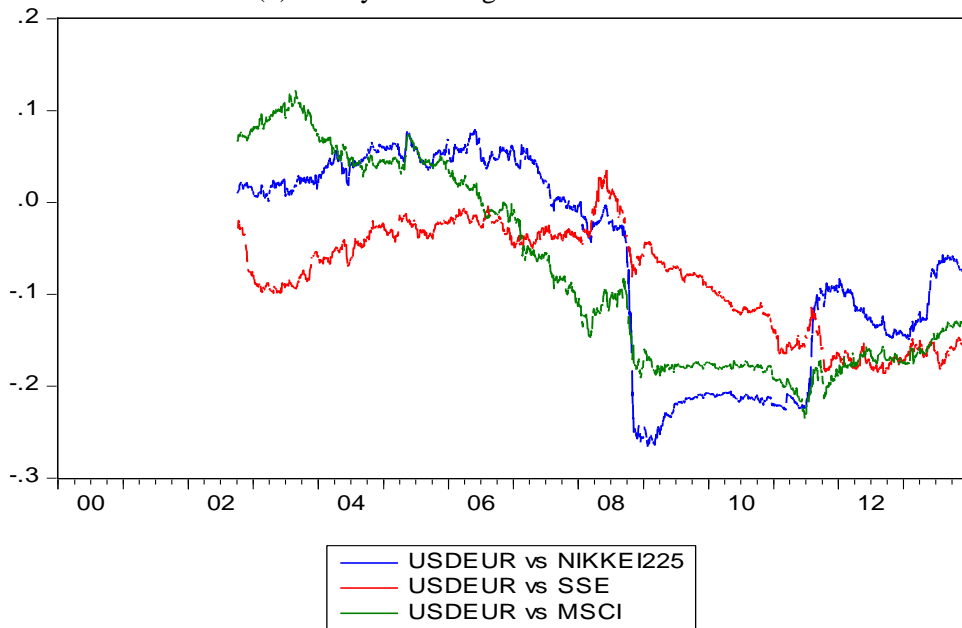
(a) Four-month rolling correlation

(b) Eight-month rolling correlation

(c) One-year rolling correlation

USDEUR vs NIKKEI225
USDEUR vs SSE
USDEUR vs MSCI

(d) Two-year rolling correlation

USDEUR vs NIKKEI225
USDEUR vs SSE
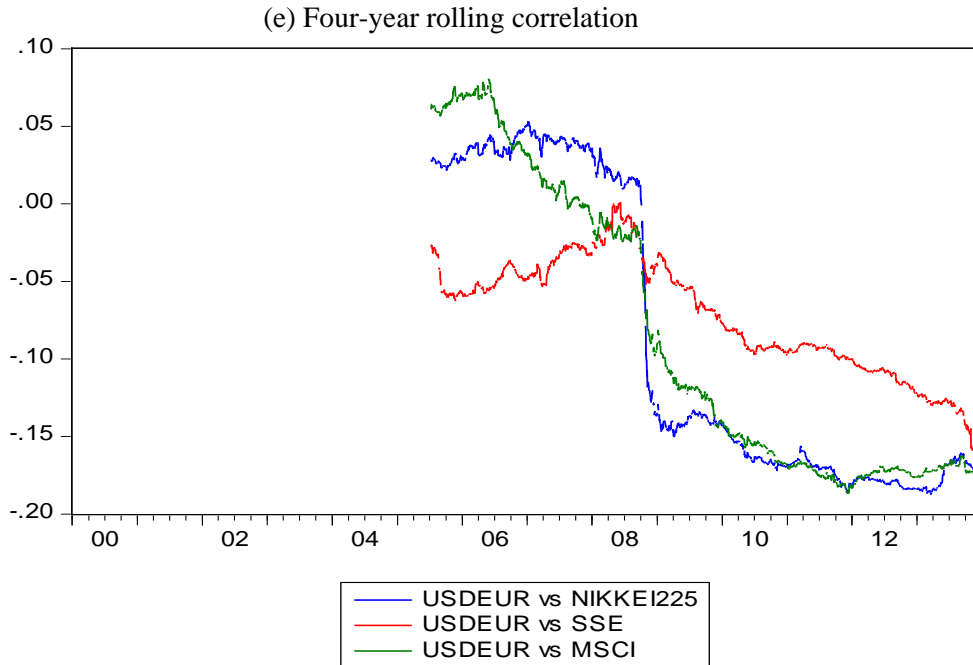USDEUR vs MSCI

(e) Four-year rolling correlation

Figure 4: Rolling correlations between exchange rate and stock index pair. (a) Four-month rolling correlation. (b) Eight-month rolling correlation. (c) Two-year rolling correlation. (d) Two-year rolling correlation. (e) Four-year rolling correlation.

Table 6: Empirical results of the DCC model(whole sample analysis).

	Sampleperiod (January 1, 2000-December 10, 2013)					
	Symmetric DCC			Asymmetric DCC		
	Coefficient	Std.Error	p-value	Coefficient	Std.Error	p-value
a1	0.0713***	0.0065	0.0000	0.0706***	0.0071	0.0000
b1	0.9969***	0.0006	0.0000	0.9967***	0.0008	0.0000
g1	_	_	_	-0.0332*	0.0292	0.0549
Log Likelihood	5423.36			5658.87	_	_
BIC	42949.369	_	_	42957.2111	_	_

Notes:The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively. $Q_t = (1 - a_1 - b_1)\bar{Q} - g_1\bar{N} + a_1 Z_{t-1} Z'_{t-1} + b_1 Q_{t-1} + g_1 \eta_{t-1} \eta'_{t-1}$ where Q_t is the conditional covariance matrix between the standardized residuals; z_t is the matrix of the standardized residuals; $\bar{Q}$ and $\bar{N}$ are the unconditional correlation matrices of z_t; $\eta_t = I[Z_t < 0] \circ Z_t$ and $I[.]$ is a $k \times 1$ indicator function such as $I = 1$ if $Z_t < 0$ and $I = 0$ if $Z_t \geq 0$, while "$\circ$" is the Hadamard product.

Figure 5 plots the estimated DCCs between each pair of the exchange rate and stock prices. First, the time path of the DCC series fluctuates over the whole sample period for all pairs, thereby suggesting that the assumption of constant correlations may not be appropriate. This result is generally in line with empirical studies such as Perez-Rodriguez (2006) and Tamakoshi and Hamori (2014). Second, the estimated DCCs between all pairs remain at a relatively high level (i.e., above 0.9) before 2007. This implies the development of a considerable degree of market integration, which has occurred since the inception of the euro. Third, the DCC series between all pairs of exchange rate and stock prices show sharp

declines during the financial crisis since 2007 and further declines since late 2009 in particular.

(F) The DCC between the USDEUR and NIKKEI225
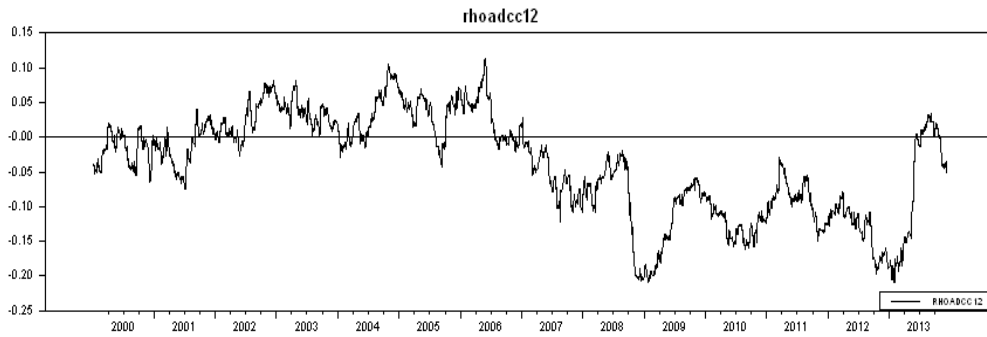
(G) The DCC between the USDEUR and SSE
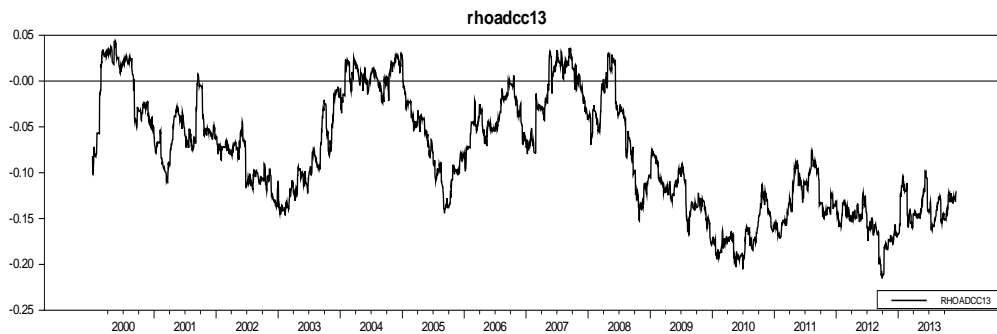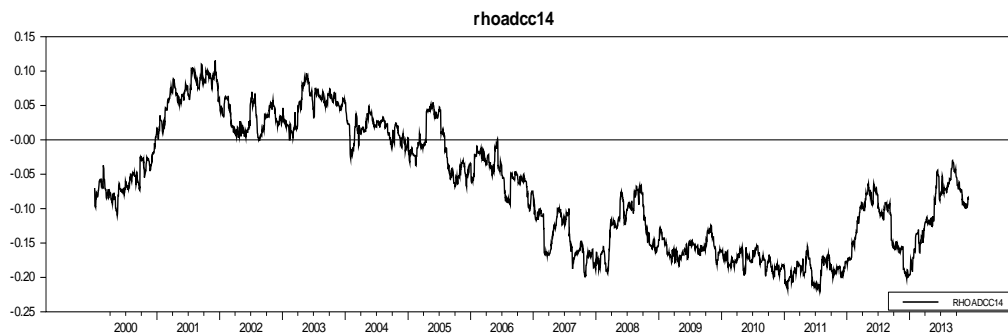

(H) The DCC between the USDEUR and MSCI

Figure 5: Dynamic conditional correlations between each foreign exchange rate and stock prices pair. (a) The DCC between the USDEUR and NIKKEI225. (b) The DCC between the USDEUR and SSE. (c) The DCC between the USDEUR and MSCI.

5 The DCC Behavior during different Phases of the Global Financial and European Sovereign Debt Crises

In what follows, we examine the DCCs shifts behavior during different phases of the global financial and European sovereign debt crises. In order to identify which of the sub-periods exhibit significant linkages among the selected stock prices and foreign exchange rate, we create numerous dummy variables, which are equal to unity for the corresponding phase of the crisis and zero otherwise. In order to describe the behavior of the DCCs over time, the dummies are created to the following mean equation:

$$\rho_{ij,t} = \omega_{ij} + \sum_{p=1}^{P} \varphi_p \rho_{ij,t-p} + \sum_{k=1}^{\lambda} \beta_k dummy_{k,t} + e_{ij,t} \tag{23}$$

where ω_{ij} is a constant term, $\rho_{ij,t}$ is the pair-wise conditional correlation of the exchange rate and three stock prices, such that $i, j =$USDBRL, NIKKEI225, SSE, and MSCI($i \neq j$), and $k = 1, ..., \lambda$ are the number of dummy variables corresponding to the different phases of the two crises, which are identified based on the economic approach. Optimal lag length (p) is selected by Akaike (AIC) and Schwarz (SIC) information criterion. Based on the economic approach, $dummy_{k,t}$ $(k = 1,2, ...,6)$ corresponds to the four phases of the global financial crisis and the two phases of the European sovereign debt crisis.

Next, we examine whether the conditional variance equation of the DCCs series exhibit symmetries or asymmetries behavior following Engle and Ng (1993). These authors propose a set of tests for asymmetry in volatility, known as sign and size bias tests. The Engle and Ng tests should thus be used to determine whether an asymmetric model is required for a given series, or whether the symmetric GARCH model can be deemed adequate. In practice, the Engle-Ng tests are usually applied to the residuals of a GARCH fit to the returns data.

Define S_{t-1}^{-} as an indicator dummy variable such as:

$$S_{t-1}^{-} = \begin{cases} 1 & if \ \ \hat{z}_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases} \tag{24}$$

The test for sign bias based on the significance or otherwise of ϕ_1 in the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^{-} + v_t \tag{25}$$

where v_t is an independent and identically distributed error term. If positive and negative shocks to $\hat{z}_{t-1}$ impact differently upon the conditional variance, then ϕ_1 will be statistically significant.

It could also be the case that the magnitude or size of the shock will affect whether the response of volatility to shocks is symmetric or not. In this case, a negative size bias test would be conducted, based on a regression where S_{t-1}^{-} is used as a slope dummy variable. Negative size bias is argued to be present if ϕ_1 is statistically significant in the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- z_{t-1} + \nu_t \tag{26}$$

Finally, we define $S_{t-1}^+ = 1 - S_{t-1}^-$, so that S_{t-1}^+ picks out the observations with positive innovations. Engle and Ng (1993) propose a joint test for sign and size bias based on the following regression:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- z_{t-1} + \phi_3 S_{t-1}^+ z_{t-1} + \nu_t \tag{27}$$

Statistical significance of ϕ_1 indicates the presence of sign bias, where positive and negative shocks have differing impacts upon future volatility, compared with the symmetric response required by the standard GARCH formulation. However, the significance of ϕ_2 or ϕ_3 would suggest the presenceof size bias, where not only the sign but the magnitude of the shock is important. A joint test statistic is formulated in the standard fashion by calculating TR^2 from regression (27), which will asymptotically follow a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects.

Table 7 reports the results of Engle-Ng tests. As shown in the table, the $\chi^2(3)$ joint test statistics demonstrates a very acceptance of the null of no asymmetries for the $\rho_{usdeur-nikkei225}$, and $\rho_{usdeur-sse}$ and $\rho_{usdeur-msci}$ series (AR(0)-FIAPARCH(1,d,1) model) and a rejection for the null hypothesis for the $\rho_{usdeur-nikkei225}$, , $\rho_{usdeur-sse}$, and $\rho_{usdeur-msci}$ series (AR(0)-EGARCH(1,1) model). The results overall would thus suggest motivation for estimating symmetric and asymmetric GARCH volatility models, respectively, for these particular series.

Table 7: Tests for sign and size bias for DCCs.

| Variable | AR(0)-EGARCH(1,1) | | | | | |
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
ϕ_0	1.3522	0.3385	2.3657***	0.0000	1.0675**	0.0182
ϕ_1	-0.7688	0.59001	-1.529***	0.0005	-0.5887	0.2173
ϕ_2	-0.706***	0.0003	-0.2395*	0.0651	-0.779***	0.0000
ϕ_3	-2.0691	0.5481	-7.513***	0.0000	-0.4772	0.6662
$\chi^2(3)$	13.4475***	0.0037	19.8351***	0.0001	32.0432***	0.0000

Note: The superscripts ***, ** and * denote the statistical significance at 1% and 5% levels, respectively.

Table 7 (continued): Tests for sign and size bias for DCCs.

| Variable | AR(0)-FIAPARCH(1,d,1) | | | | | |
	Coefficient	p-value	Coefficient	p-value	Coefficient	p-value
ϕ_0	1.0356***	0.0000	0.8447***	0.0000	1.3492***	0.0000
ϕ_1	-0.0362	0.7642	0.1899	0.1506	-0.428***	0.0000
ϕ_2	0.0144	0.8776	0.0271	0.7265	-0.0774	0.3188
ϕ_3	-0.0231	0.7627	0.1467	0.1732	-0.348***	0.0000
$\chi^2(3)$	0.4488	0.9299	2.4501	0.4843	2.9656	0.2900

Note: The superscripts ***, ** and * denote the statistical significance at 1% and 5% levels, respectively.

Furthermore, the conditional variance equations of the $\rho_{usdeur-nikkei225}$, , $\rho_{usdeur-sse}$, and $\rho_{usdeur-msci}$ series are assumed to follow an asymmetric GARCH specification under a student distributed innovations (AR(0)-EGARCH(1,1) model). In our analysis, we choose the student-t-GJR-GARCH(1,1) model (see Glosten et al.,1993) including the dummy variables identified by the two approaches:

$$h_{ij,t} = \alpha_0 + \alpha_1 h_{ij,t-1} + \sum_{k=1}^{\lambda} \xi_k dummy_{k,t} + \nu_1 e_{ij,t-1}^2 + \alpha_2 e_{ij,t-1}^2 I(e_{ij,t-1} < 0) \qquad (28)$$

Moreover, the conditional variance equations of the $\rho_{usdeur-nikkei225}$, , $\rho_{usdeur-sse}$ series are assumed to follow a symmetric student-t-GARCH (1,1) specification (AR(0)-FIAPARCH(1,d,1) model).

$$h_{ij,t} = \alpha_0 + \alpha_1 h_{ij,t-1} + \nu_1 e_{ij,t-1}^2 + \sum_{k=1}^{\lambda} \xi_k dummy_{k,t} \qquad (29)$$

Table 8: Tests of changes in dynamic conditional correlations among exchange rate and stock market returns during the phases of global financial and European sovereign debt crises (AR(0)-GJR-GARCH(1,1) approach).

Variable	$\rho_{usdeur-nikkei225}$		$\rho_{usdeur-sse}$		$\rho_{usdeur-msci}$	
	Coeff	Signif	Coeff	Signif	Coeff	Signif
Mean Equation						
ω	-0.0001***	0.0000	-0.0002***	0.0000	-0.0001**	0.0372
β_1	0.0002	0.1696	0.0004***	0.0000	-5E-05***	0.0000
β_2	-0.0005*	0.0566	0.0002	0.3713	-0.0002	0.7879
β_3	-0.0002	0.2620	-0.0001	2.0042	-0.0004	0.4181
β_4	0.0003**	0.0240	-0.0003	0.3697	-0.0002**	0.0348
β_5	-0.0004**	0.0339	-0.0001	0.3554	-0.0003	0.2036
β_6	-0.0001***	0.0052	-0.0001	0.8475	-0.0002*	0.0894
Variance Equation						
α_0	-2.2328***	0.0000	-2.9834	0.4836	-2.366*	0.0566
α_1	0.1083***	0.0000	0.1104	0.2714	0.1055***	0.0000
ν_1	0.5111***	0.0000	0.5487***	0.0000	0.5616***	0.0000
α_2	-0.0117***	0.0000	-0.0423***	0.0000	-0.0219***	0.0000
ξ_1	0.1035**	0.0476	0.1263***	0.0000	0.0047***	0.0000
ξ_2	0.2700***	0.0092	0.1298***	0.0000	-0.1175	0.9143
ξ_3	-0.1224	0.3098	-0.2236**	0.0192	-0.2666	0.2706
ξ_4	-0.1244*	0.0793	0.0275	0.2681	-0.1998**	0.0126
ξ_5	-0.18553**	0.0146	-0.0447*	0.0550	-0.1476***	0.0002
ξ_6	-0.0641***	0.0000	-0.0548	0.6930	-0.0733**	0.0241
ν	2.0008***	0.0000	2.0042	0.4878	2.0017***	0.0000
Diagnostics						
$LB(20)$	192.726***	0.0000	175.002***	0.0000	139.467***	0.0000
$LB^2(20)$	0.4468	1.0000	29.8808**	0.0386	1.8675	0.9999

Notes: Estimates are based on mean Eq. (23) and variance Eq. (28) and Eq. (29) in the text. The lag length is determined by the SIC criteria (Box-Jenkins procedure). $\beta_{k,t}$ and $\xi_{k,t}$, where $k = 1, 2, 3, 4, 5, 6$, are the dummy variable coefficients corresponding to the four phases of the global financial crisis and the two phases of the European sovereign debt crisis. α_1 is the coefficient of h_{t-1} and α_2 is the asymmetric (GJR) term. $LB(20)$ and $LB^2(20)$ denote the Ljung-Box tests of serial correlation on both standardized and squared standardized residuals.***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

According to Eqs. (23) and (28) (respectively Eqs. (23) and (29)), we could analyze whether

each phase of the global financial and European sovereign debt crises significantly alter the dynamics of the estimated DCCs and their conditional volatilities. In other words, the statistical significance of the estimated dummy coefficients indicates structural changes in mean and/or variance shifts of the correlation coefficients due to external shocks during the different periods of the two crises. According to Dimitriou and Kenourgios (2013), a positive and statistically significant dummy coefficient in the mean equation indicates that the correlation during a specific phase of the crisis is significantly different from that of the previous phase, supporting the presence of spillover effects among stock prices and exchange rate. This implies that the benefits from portfolio diversification strategies diminish. Furthermore, a positive and statistically significant dummy coefficient in the variance equation indicates a higher volatility of the correlation coefficients. This suggests that the stability of the correlation is less reliable, causing some doubts on using the estimated correlation coefficient as a guide for portfolio decisions.

Table 8 reports the estimation results of the AR(0)-GJR-GARCH(1,1) model.At the phase 2 of the global financial crisis, the dummy coefficient (β_2) is negative and statistically significant for the pair of USDEUR-NIKKEI225, supporting a decrease in DCCs.Nevertheless, the β_2 parameter is positive and statistically no significant for the pair of USDEUR-SSE, indicating the absence of a "contagion effect". Moreover, this parameter is negative and no significant for the pair of USDEUR-MSCI, supporting an increase in DCCs.During the phase 3 of macroeconomic deterioration, negative and statistically no significant dummy coefficients β_3 exist for each pairs, implying a decrease of DCCs and thus suggesting that the relationship among these currencies is actually decreased during this phase. This result can be viewed as a "contagion effect".

Table 9: Tests of changes in dynamic conditional correlations among exchange rate and stock market returns during the phases of global financial and European sovereign debt crises (AR(0)-GARCH(1,1) model).

Variable	$\rho_{usdeur-nikkei225}$		$\rho_{usdeur-sse}$		$\rho_{usdeur-msci}$	
	Coeff	Signif	Coeff	Signif	Coeff	Signif
Mean Equation						
ω	-0.0001**	0.0114	-0.0002***	0.0000	-0.0001*	0.0510
β_1	0.0001	0.2596	0.0003	0.8130	-0.0003	0.8647
β_2	-0.0005	0.1639	0.0002	0.2968	-0.0001	0.5946
β_3	-0.0003	0.3057	-0.0001	0.4338	-0.0003	0.1851
β_4	0.0003	0.1080	-0.0002	0.8861	-0.0002	0.2320
β_5	-0.0004**	0.0354	-0.0001	0.4485	-0.0003*	0.0960
β_6	-0.0001	0.1901	-0.0001	0.3198	-0.0002	0.1009
Variance Equation						
α_0	0.0012***	0.0001	0.0002***	0.0000	0.0001***	0.0000
α_1	-0.5516**	0.0246	0.1603*	0.0532	-0.3857***	0.0000
ν_1	0.3474	0.1596	0.8476***	0.0000	0.9973***	0.0000
ξ_1	0.0003	0.1244	0.0008*	0.0633	0.0004	0.1685
ξ_2	0.0008	0.1325	0.0001	0.2759	-0.0002*	0.0589
ξ_3	-0.0002	0.2538	-0.0001***	0.0020	0.0001	0.9163
ξ_4	-0.0002*	0.0901	0.0001	0.7587	-0.0005	0.2452
ξ_5	-0.0004*	0.0510	0.0003	0.9504	0.0003	0.9500
ξ_6	-0.0001	0.1543	-0.0002	0.2081	-0.0002**	0.0120
ν	2.0044***	0.0000	2.0033***	0.0000	2.0036***	0.0000
Diagnostics						
$LB(20)$	2780.81***	0.0000	60.5135	0.9706	5908.16***	0.0000
$LB^2(20)$	10.2637	0.9229	14.2764	0.8658	19.3384	0.7385

Notes:Estimates are based on mean Eq. (23) and variance Eq. (28) and Eq. (29) in the text.

The lag length is determined by the SIC criteria (Box-Jenkins procedure). $\beta_{k,t}$ and $\xi_{k,t}$, where $k = 1, 2, 3, 4, 5, 6$, are the dummy variable coefficients corresponding to the four phases of the global financial crisis and the two phases of the European sovereign debt crisis. α_1 is the coefficient of h_{t-1} and α_2 is the asymmetric (GJR) term. $LB(20)$ and $LB^2(20)$ denote the Ljung-Box tests of serial correlation on both standardized and squared standardized residuals.***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

During the last phase of the European sovereign debt crisis, significantly negative dummy coefficients (β_6) correspond to the pair of USDEUR-NIKKEI225 and USDEUR-MSCI. Finally, the dummy coefficients' estimates of the variance Eq. (29), are negative and statistically significant in most cases cross several phases of the global financial and European sovereign debt crises. This finding indicates a more stable structure of correlation, suggesting the use of the correlation coefficients as a guide for portfolio decisions during specific phases of the two crises. However, the dummy coefficients ξ_1 for each pairs, ξ_2 for USDEUR-NIKKEI225 and USDEUR-SSE are positive and statistically significant. This means that the volatility of correlation coefficients is increased, implying that the stability of the correlations is less reliable for the realization of investment strategies. The dummy coefficient ξ_4, ξ_5 and ξ_6 for USDEUR-NIKKEI225 and USDEUR-MSCI are negative and no significant, suggesting that the volatility of correlation coefficients is decreased, implying that the stability of the correlations is more reliable for the realization of investment strategies.

The estimation results of the AR(0)-GARCH(1,1) model are displayed in Table 9. The constant terms ω_{ij} is statistically significant for all pairs. At the phase 2 of the global financial crisis, the dummy coefficients (β_2) is negative and statistically no significant for only the pair of USDEUR-NIKKEI225 and USDEUR-MSCI, supporting a decrease in DCCs. During the phase 3 of macroeconomic deterioration, negative and statistically no significant dummy coefficients β_3 exist for each pairs, implying a decrease of DCCs and thus suggesting that the relationship among these currencies is actually decreased during this phase. This result can be regarded as a "contagion effect".

The first phase of ESDC exhibits only one case of significantly negative dummy coefficients (β_5) for the pair of USDEUR-NIKKEI225 and USDEUR-MSCI. This period is characterized by a sharp depreciation of EUR due to the "Greek problem" and the uncertainty about the future of euro as a single Eurozone currency. This finding can be viewed as a "contagion effect" as both foreign exchange rate and stock prices seem to be substantially influenced by the European sovereign debt crisis.

Finally, the dummy coefficients' estimates of the variance Eq. (29), are either positive or negative and statistically significant or no significant in most cases across several phases of the global financial and European sovereign debt crises. The no significant positive dummy coefficients ξ_k means that the volatility of correlation coefficients is increased, implying that the stability of the correlations is less reliable for the implementation of investment strategies. However, the significant negative dummy coefficients ξ_k indicates a more stable structure of correlation, suggesting the use of the correlation coefficients as a guide for portfolio decisions during specific phases of the global financial and European sovereign debt crises.

6   Conclusion

While time varying correlations of stock market returns and foreign exchange rate have seen voluminous research, relatively little attention has been given to the dynamics of correlations within a market.

In this paper, we analyze the dynamic conditional correlation between the US dollar (USD) exchange rates expressed in Euro (EUR) and three stock markets using a DCC model into a multivariate fractionally integrated APARCH framework (FIAPARCH-DCC model), which provides the tools to understand how financial volatilities move together over time and across markets, and the Asymmetric Dynamic Conditional Correlation (A-DCC) model developed by Cappiello et al. (2006). We also use an AR-GARCH model for statistical analysis of the time-varying correlations by considering the major financial and economic events relative to the subprime crisis and global financial crisis.

The FIAPARCH model is identified as the best specification for modeling the conditional heteroscedasticity of individualtime series.We then extended the above univariate GARCH models to a bivariate framework with dynamic conditional correlation parameterization in order to investigate the interaction between stock markets and exchange rate.

Our empirical results indicate that foreign exchange market and european stock markets exhibit asymmetry and no asymmetry in the conditional variances. Therefore, the results point to the importance of applying an appropriately flexible modeling framework to accurately evaluate the interaction between exchange market and stock market co-movements. the conditional correlation among the USD/EUR and the three stock index exhibits higher dependency when it is driven by negative innovations to changes than it is by positive innovations. Moreover, the stock market and foreign exchange rate correlations become more volatile during the global financial crisis. Moreover, results document strong evidence of time-varying comovement, a high persistence of the conditional correlation (the volatility displays a highly persistent fashion) and the dynamic correlations revolve around a constant level and the dynamic process appears to be mean reverting.

Our empirical findings seem to be important to researchers and practitioners and especially to active investors and portfolio managers who include in their portfolios equities from the European exchange markets. Indeed, the high correlation coefficients, during crises periods, imply that the benefit from international diversification, by holding a portfolio consisting of diverse stocks from the contagious stock markets, decline.

The findings lead to important implications from investors' and policy makers' perspective. They are of great relevance for financial decisions of international investors on managing their risk exposures to exchange rate and stock prices fluctuations and on taking advantages of potential diversification opportunities that may arise due to lowered dependence among the exchange rates and stock prices. The increase of exchange rates and stock prices linkages during crisis periods shows the different vulnerability of the currencies and implies a decrease of portfolio diversification benefits, since holding a portfolio with diverse currencies is less subject to systematic risk. Moreover, this correlations' behavior may be considered as evidence of non-cooperative monetary policies around the world and highlight the need for some form of policy coordination among central banks. Finally, the different patterns of dynamic linkages among stock prices and exchange rate may influence transnational trade flows and the activities of multinational corporations, as they create uncertainty with regard to exports and imports.

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