

On the Comovements among European Exchange Rates and Stock Prices: A Multivariate Time-Varying Asymmetric Approach

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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 European stock prices (DAX30, CAC40 and FTSE100). Focusing on different phases of the Global financial crisis (GFC) and the Eurozone Sovereign Debt Crisis (ESDC), we adopt a multivariate asymmetric dynamic conditional correlation EGARCH framework, during the period spanning from January 1, 2002 until December 10, 2013. The empirical results suggest asymmetric responses in correlations among the three European stock prices and exchange rate. Moreover, the results indicate an increase of exchange rates and stock prices correlations during the crisis periods, suggesting the different vulnerability of the currencies. Finally, we find some significant decreases in the estimated dynamic correlations, indicating existence of a “currency contagion effect” during turmoil periods.

JEL classification numbers: C13, C22, C32, C52, C53, G15.

Keywords: A-DCC model, Global financial crisis, European sovereign debt crisis, exchange rates, stock prices and currency contagion.

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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.

The dynamic relationships between exchange rate movements and stock prices have attracted a special attention from both practitioners and academics. A strong relationship between them would have important implications for international capital budgeting decisions and economic policies because negative shocks affecting one market may be transmitted quickly to another through contagious effects. This issue has become more critical with the occurrence of recent black swan events such as the US 2007 subprime crisis. 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.

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 analyse 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.

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)).

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-Rodriguez, 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.

Furthermore, it would be interesting to conduct an empirical analysis on how the dependence structures of the three European stock prices and the exchange rate (USD/EUR) changed particularly during the recent global financial and Euro zone sovereign debt crises. Two major contributions on this topic are made in the present study. First, we investigate the asymmetric behavior of dynamic correlations among exchange rate and stock prices by employing the multivariate asymmetric DCC (A-DCC) model put forward by Cappiello et al. (2006). 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. Second, we evaluate how the global financial and European sovereign debt crises influenced the estimated DCCs among the currency markets.

The layout of the present study is as follows. Section 2 presents the empirical methodology and the identification of the length and the phases of the two crises. Section 3 provides the data and a preliminary analysis. Section 4 presents and discusses the tests for sign and size bias. The empirical results are displayed, analyzed and discussed in section 5, while section 6 reports the concluding remarks.

2 Econometric Methodology

2.1 AG-DCC-EGARCH Model

To investigate the dynamics of the correlations between American exchange rate expressed in (EUR) and three European stock markets namely Germany (DAX30), France (CAC40) and United Kingdom (FTSE100), 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) and Toyoshima and Hamori (2013)). In the first step, we estimate the conditional variances of exchange rate and stock market returns using an autoregressive- asymmetric exponential generalized autoregressive conditional heteroscedasticity ($AR(m) - EGARCH(p, q)$) model². For a more detailed analysis, we use the following equations:

$$r_t = \mu_0 + \sum_{i=1}^m \mu_i r_{t-i} + \varepsilon_t \quad (1)$$

$$\ln(h_t) = \omega + \sum_{i=1}^q [\alpha_i |z_{t-i}| + \gamma_i z_{t-i}] + \sum_{i=1}^p \beta_i \ln(h_{t-i}) \quad (2)$$

where r_t indicates stock returns and exchange rate return, 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. There is thus 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.

We assume that the random variable z_t has a student distribution (see Bollerslev (1987)) with $\nu > 2$ degrees of freedom with a density given by:

$$D(z_t, \nu) = \frac{\Gamma(\nu + \frac{1}{2})}{\Gamma(\frac{\nu}{2}) \sqrt{\pi(\nu - 2)}} \left(1 + \frac{z_t^2}{\nu - 2}\right)^{-\frac{1}{2}\nu} \quad (3)$$

where $\Gamma(\nu)$ is the gamma function and ν is the parameter that describes the thickness of the distribution tails. The Student distribution is symmetric around zero and, for $\nu > 4$, the conditional kurtosis equals $3(\nu - 2)/(\nu - 4)$, which exceeds the normal value of three. For large values of ν , 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 positive. The term $\sum_{i=1}^p \beta_i$ measures the persistence of shocks to the conditional variance.

The conditional mean equation (Eq. 1) is specified as an autoregressive process of order m . The optimal lag length m for each asset return series is given by the Schwartz-Bayesian Information Criterion (SBIC). (Eq. 2).represents the conditional variance and is specified as and $EGARCH(p, q)$ process. The optimal lag lengths p and q are

²See Nelson (1991).

determined by employing the SBIC criterion.

From Eq. 2, we first obtain the conditional volatilities and then recover the conditional correlations. The conditional covariance matrix is then defined as follows:

$$H_t = D_t R_t D_t \quad (4)$$

where the diagonal matrix D_t is the conditional standard deviation obtained from Eq. 2. 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

$$Q_t = (\bar{Q} - A' \bar{Q} A - B' \bar{Q} B - G' \bar{N} G) + A' Z_{t-1} Z_{t-1}' A + B' Q_{t-1} B + G' \eta_{t-1} \eta_{t-1}' G \quad (5)$$

where \bar{Q} and $\bar{N} = E(\eta_t \eta_t')$ are the unconditional correlation matrices of Z_t and η_t . $\eta_t = I[Z_t < 0] \circ Z_t$. $I[\cdot]$ 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:

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \quad (6)$$

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

2.2 Crisis Periods Specification

The recent global financial crisis and European sovereign debt crisis have some unique features, such as the length, breadth and crisis sources. Numerous studies use major economic and financial events in order to determine the crisis length and source ad-hoc (see Forbes and Rigobon, 2002; Chiang et al., 2007, among others). Nevertheless, other studies follow a statistical approach using Markov regime switching processes to identify the crisis period endogenously (see Boyer et al., 2006; Rodriguez, 2007, among others). Note that both economic and statistical approaches are at least in some degree arbitrary. Some studies avoid discretion in the definition of the crisis period by using discretion in the choice of the econometric model to estimate the location of the crisis period in time. Baur (2012) uses both key financial and economic events and estimates of excess volatility to identify the crisis period and investigates the transmission of the global financial crisis from the financial sector to real economy.

In this study, we specify the length of both global financial and sovereign debt crises and their phases following both the economic and statistical approaches. First, we define a relatively long crisis period based on all major international financial and economic news events representing both crises. We use the official timelines provided by Federal Reserve

Board of St. Louis (2009) and the Bank for International Settlements (BIS, 2009), among others, in order to choose the crisis period. According to these studies, the timeline of the global financial crisis is separated in four phases. Phase 1 described as “initial financial turmoil” spans from August 1, 2007 to September 15, 2008. Phase 2 is defined as “sharp financial market deterioration” and spans from September 16, 2008 to December 31, 2008. Phase 3 described as “macroeconomic deterioration” spans from January 1, 2009 until March 31, 2009. Phase 4 described as a phase of “stabilization and tentative signs of recovery” (post-crisis period) and including a financial market rally, spans from April 1, 2009 until November 4, 2009.

Using the European central bank (ECB)³ and Reuters⁴ timelines, the European Sovereign Debt crisis timeline⁵ is constructed as follows. Phase 1 spans from November 5, 2009 until April 22, 2010. It begins when Greece revealed that its budget deficit was 12.7% of gross domestic product (GDP), more than twice what the country had previously disclosed, leading to a sharp increase of the regional sovereign risk. Phase 2 spans from April 23, 2010 onwards until the end of the sample period. It triggered shortly before the EU-IMF bailout of Greece in May 2010, when the Greek Prime Minister announced that the austerity packages are not enough and requested for a bailout plan from the Eurozone and the IMF.

In order to identify regimes of excess exchange rate conditional volatility (h_{it}) and stock price conditional volatility, we follow a statistical approach based on a Markov Switching Dynamic Regression (MS-DR)⁶ model, which takes into account endogenous structural breaks and thus allows the data to determine the beginning and end of each phase of the crises. Stock prices and exchange rates’ conditional volatilities are obtained from estimating the univariate AR(0)–EGARCH(1,1) model during the entire sample period. This model can be used to identify the crises periods endogenously and thus allows the data to determine the beginning and end of each phase of the crises. The MS-DR model assumes the existence of two regimes (“stable” and “volatile”), where the regime 0 (“stable” regime) defines the lower values of h_{it} and the regime 1 (“volatile/crisis regime”) their higher values.

The smoothed regime probabilities of h_{it} depicted in Fig. 1 reveal that that the “volatile”/crisis regimes for each examined currency are all located within the crisis period based on economic and financial news events described above.

³<http://www.ecb.int/ecb/html/crisis.en.html>.

⁴<http://www.reuters.com/article/2010/08/25/eurozone-crisis-events-idUSLDE67O0YD20100825>.

⁵Constancio (2012), Kalbaska and Gatkowski (2012), and Arghyrou and Kontonikas (2012), among others, use a similar timeline for the European sovereign debt crisis.

⁶In MS-DR model, the lags of the dependent variable are added in the same way as other regressors. An example is:

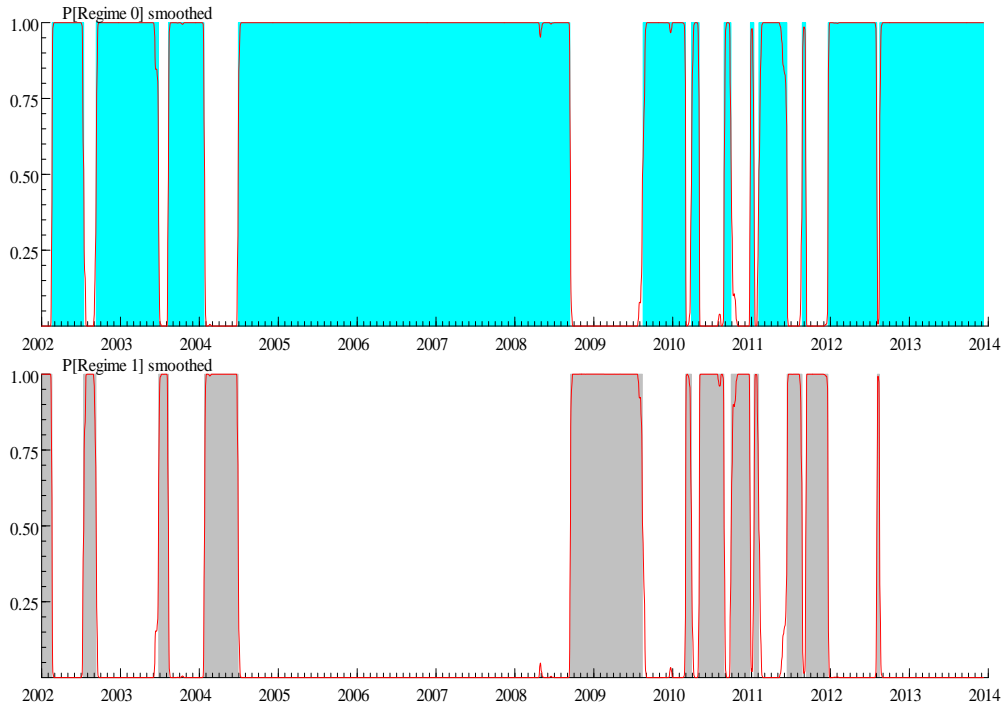
$$y_t = v(s_t) + \alpha y_{t-1} + X_t' \beta + \varepsilon_t \quad \text{where } \varepsilon_t \rightarrow N(0, \sigma^2)$$

s_t is the random variable denoting the regime. If there are two regimes, we could also write:

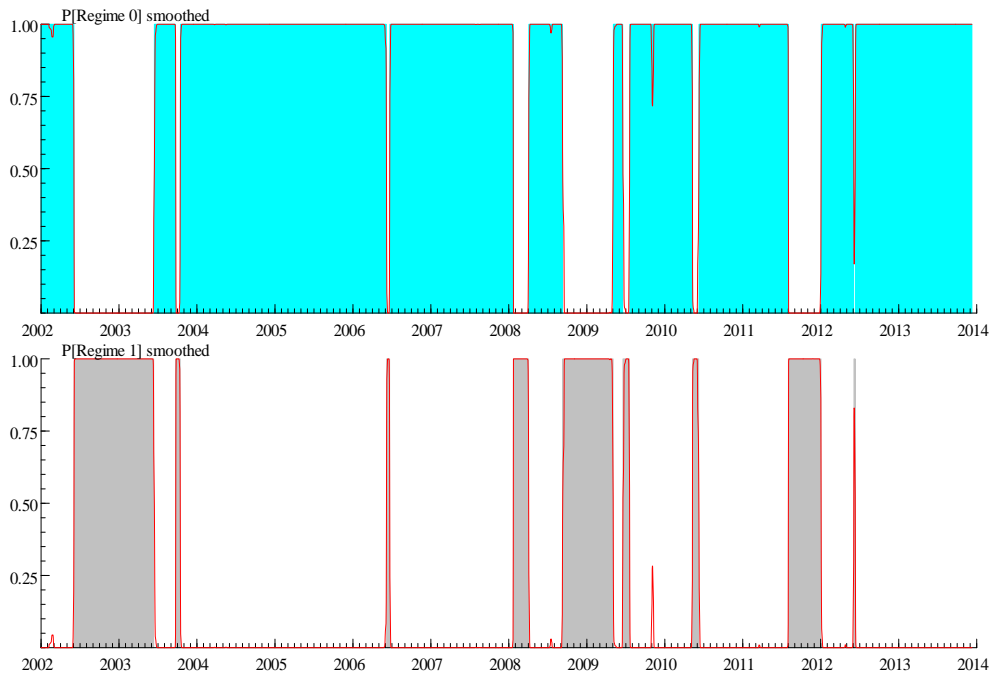
- Regime 0: $y_t = v(0) + \alpha y_{t-1} + X_t' \beta + \varepsilon_t$
- Regime 1: $y_t = v(1) + \alpha y_{t-1} + X_t' \beta + \varepsilon_t$

which shows the regime dependent intercept more clearly.

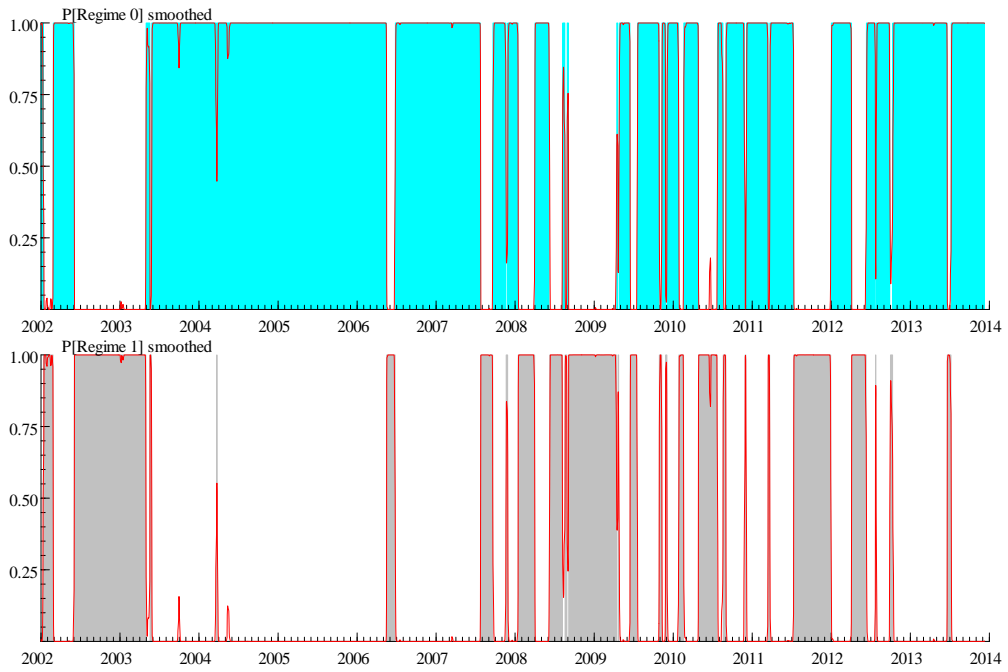
USD/EUR



DAX30



CAC40



FTSE100

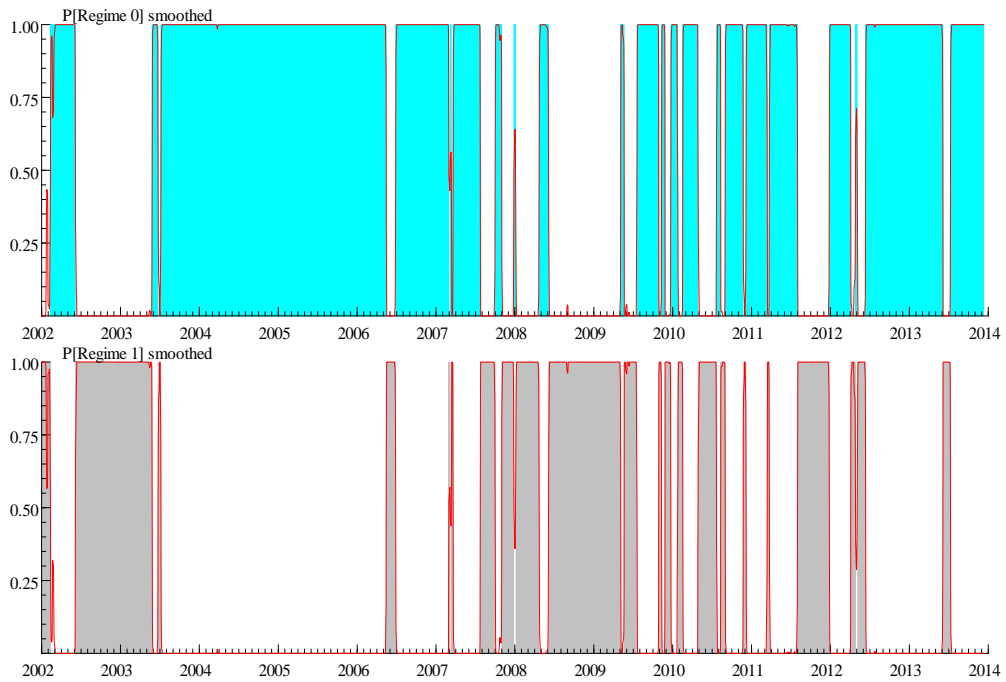


Figure 1: Regime classification of stock index and exchange rates' conditional volatilities (h_{it}).

Notes: Regime 0, in light blue, corresponds to periods of stable and low volatility. Regime

1, in grey, denotes periods of rising and persistent volatility returns. The red columns indicate the smoothed regime probabilities, while the grey shaded spaces are the regimes of excess volatilities according to MS-DR model.

3 Data and Preliminary Analyses

The data comprises daily American exchange rates expressed in (EUR) of the European foreign currencies and daily stock prices for three major European countries. All data are sourced from the Board of Governors of the Federal Reserve System and (<http://www.econstats.com>). We use daily data not only to secure a sufficient number of observations for examining the recent global financial and European sovereign debt crises, but also to avoid the inefficiency that might arise if smaller samples are applied to a time-varying parameter method such as the A-DCC model.

The sample covers a period from January 01, 2002 until December 10, 2013, leading to a sample size of 3116 observations. For each currency, the continuously compounded return is computed as: $r_t = 100 * \ln\left(\frac{p_t}{p_{t-1}}\right)$ for $t = 1, 2, \dots, T$, where p_t is the price on day t .

Table 1 reports the descriptive statistics for our data set. DAX30 exhibits the largest positive mean return, thereby suggesting that the stock price is most significantly. Moreover, the positive mean return for USD/EUR indicate the depreciation of the currency and the negative mean return for CAC40 indicate the appreciation of the currency. In addition, the standard deviation or volatility of DAX30 is the highest over the sample period. The higher levels of Skewness for USDEUR and CAC40 indicate that extreme variations tend to occur more frequently for these currencies. Besides, there exist fat tails in the return distribution according to the high values of kurtosis for all stock prices. To accommodate the existence of “fat tails”, we assume student-t distributed innovations. Furthermore, the Jarque-Bera statistic rejects normality assumption at the 1% level for all for all stock prices and exchange rate. This finding indirectly supports the existence of an ARCH effect in the distribution of exchange rate and stock market returns.

Table 1: Descriptive statistics for exchange rate and stock market returns.

	USDEUR	DAX30	CAC40	FTSE100
Panel A: descriptive statistics				
Mean	0.0139	0.0182	-0.0039	0.0071
Maximum	4.6208	10.797	10.5950	9.3842
Minimum	-3.0031	-7.4335	-9.4715	-9.2646
Std. Deviation	0.6264	1.5512	1.5196	1.2464
Skewness	0.0786***	0.0481	0.0751***	-0.1290*
	0.0728	0.2724	0.0867	0.0032
Excess Kurtosis	2.6362*	4.9423*	5.4332*	7.1486*
	0.0000	0.0000	0.0000	0.0000
Jarque-Bera	905.51*	3172.5*	3835.5*	6643.4*
	0.0000	0.0000	0.0000	0.0000
Panel B: Serial correlation and LM-ARCH tests				
<i>LB</i> (20)	29.5108**	73.6540*	69.4058*	90.1888*
	0.0781	0.0000	0.0000	0.0000
<i>LB</i> ² (20)	736.050*	34.3546**	2859.02*	3733.88*
	0.0000	0.0238	0.0000	0.0000
ARCH 1-10	25.567*	3146.25*	71.5130*	98.7560*
	0.0000	0.0000	0.0000	0.0000
Panel C: Unit Root tests				
<i>ADF test statistic</i>	-32.3705***	-34.2341***	-36.08***	-36.8778***
	-1.9409	-1.9409	-1.9409	-1.9409

Note: Stock market returns and exchange rate are in daily frequency, the superscript *, ** and *** denotes the 1%, 5% and 10% level of significance. *LB*(20) and *LB*²(20) are the 20th order Ljung-Box tests for serial correlation in the standardized and squared standardized residuals, respectively.

Fig. 2 plots the evolution of exchange market returns and european stock prices over time. The figure shows that exchange rate and stock prices trembled since 2008 with different intensity during the global financial crises. Moreover, the plot shows a clustering of larger return volatility. This means that foreign exchange markets and stock market 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 returns and stock market returns.

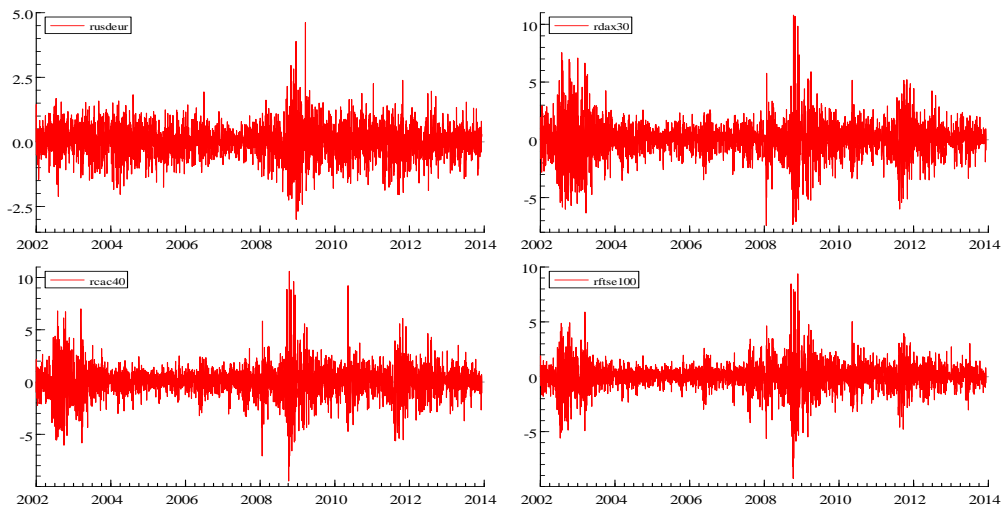


Figure 2. Exchange rates and stock market returns behavior over time.

3.1 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

$$S_{t-1}^- = \begin{cases} 1 & \text{if } \hat{z}_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases} \quad (7)$$

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

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + v_t \quad (8)$$

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:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- z_{t-1} + v_t \quad (9)$$

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:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- z_{t-1} + \phi_3 S_{t-1}^+ z_{t-1} + \nu_t \quad (10)$$

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 (10), which will asymptotically follow a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects.

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 RDAX30, RCAC40 and RFTSE100 series do not suffer from sign bias and/or negative size bias, but they do exhibit positive size bias. Second, for the RUSDEUR series, the individual regression results show that the residuals of the symmetric GARCH model exhibit sign bias, negative size bias and significant positive size bias.

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

Variables	USDEUR			DAX30			CAC40			FTSE100		
	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif	Coeff	StdError	Signif
ϕ_0	1.0296*	0.0674	0.0000	1.0369*	0.0723	0.0000	1.0558*	0.0733	0.0000	1.0948*	0.0721	0.0000
ϕ_1	0.1898*	0.0903	0.0357	0.1300	0.0984	0.1865	0.0861	0.0991	0.3850	-0.0333	0.0966	0.7302
ϕ_2	0.1802*	0.0608	0.0030	0.0181	0.063	0.7732	0.0439	0.0639	0.4918	-0.0359	0.0616	0.5602
ϕ_3	-0.169*	0.0667	0.0114	-0.2716*	0.0774	0.0004	-0.233*	0.0771	0.0025	-0.2572*	0.0759	0.0007
$\chi^2(3)$	25.5128*	_	0.0000	35.72*	_	0.0000	21.777*	_	0.0000	20.7009*	_	0.0001

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

Finally, the $\chi^2(3)$ joint test statistics for USD/EUR, DAX30, CAC40 and FTSE100 have p -values of 0.0000 and 0.0001, 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.

3.2 Empirical Results

3.2.1 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 3). This paper considers the asymmetric effect, while Tamakoshi and Hamori (2014) did not. The $AR(0) - EGARCH(1,1)$ model is chosen for all exchange rate and stock market returns. 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 3 also reports the estimates of the parameter β , which measures the degree of volatility persistence. We find that β for Germany, France and United Kingdom stock prices and (USD/EUR) exchange rate returns is 0.9949, 0.9854, 0.9817 and 0.9855 respectively. From these estimates, we could infer that the persistence in shocks to volatility is relatively large.

Table 3: AR (0)-EGARCH (1,1) estimation results.

	USDEUR			DAX30			CAC40			FTSE100		
	Coefficient	StdError	p-value	Coefficient	StdError	p-value	Coefficient	StdError	p-value	Coefficient	StdError	p-value
μ_0	0.0272*	0.0096	0.0050	0.0599*	0.0162	0.0002	0.0179	0.0178	0.3149	0.0247**	0.0127	0.0517
ω	-0.0595*	0.0091	0.0000	-0.0836*	0.0107	0.0000	-0.0724*	0.0111	0.0000	-0.0915*	0.0121	0.0000
α	0.0717*	0.01107	0.0000	0.1117*	0.0143	0.0000	0.098*	0.0142	0.0000	0.1137*	0.0156	0.0000
β	0.9949*	0.0023	0.0000	0.9854*	0.0028	0.0000	0.9817*	0.003	0.0000	0.9855*	0.0027	0.0000
γ	-0.0058	0.0072	0.4236	-0.1322*	0.0134	0.0000	-0.161*	0.0143	0.0000	-0.129*	0.0118	0.0000
Student-t parameter (ν)	8.4495*	1.3689	0.0000	8.8122*	1.4234	0.0000	10.9226*	1.9023	0.0000	10.0000*	1.6317	0.0000
Log likelihood	-2738.0844	–	–	-5028.1955	–	–	-4985.35	–	–	-4278.5048	–	–
$LB - Q(20)$	16.1262	–	0.7087	15.7351	–	0.7329	29.725*	–	0.0744	32.4955*	–	0.0382
$LB - Q^2(20)$	26.9641**	–	0.0796	23.0005	–	0.1905	15.9711	–	0.5945	12.7913	–	0.8038

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 market returns, 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 30 lags for the standardized and squared standardized residuals, respectively. The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively.

In addition, Table 3 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. As shown in the table, both statistics are not above 1%, in all cases. The null hypothesis of no autocorrelation up to order 20 for squared standardized residuals is also accepted at the 1% level of significance.

3.2.2 Asymmetric DCC results

The estimation results of the DCC and A-DCC models are reported in Table 4. We use this methodology to test the correlation among the selected three stock index and exchange rate returns. Therefore, the outcome views the interdependence between the European exchange markets and three stock indexes. 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 1% level or better, thus providing evidence of an asymmetric response in correlations. In other words, the conditional correlation among the USD/EUR and European stock prices exhibits higher dependency when it is driven by negative innovations to changes (joint appreciation) than it is by positive innovations (joint depreciation). 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 4: Empirical results of the DCC model (whole sample analysis).

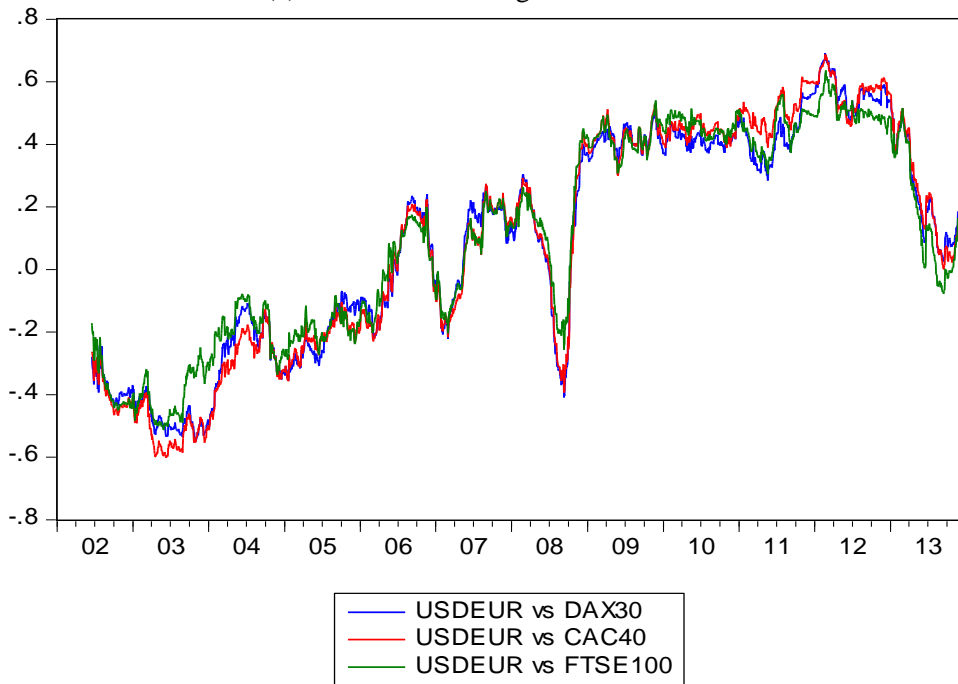
	Whole sample period (January 1, 2002-December 10, 2013)					
	Symmetric DCC			Asymmetric DCC		
	Coefficient	StdError	p-value	Coefficient	StdError	p-value
a_1	0.2087*	0.0077	0.0000	0.1871*	0.0095	0.0000
b_1	0.9678*	0.0028	0.0000	0.9690*	0.0027	0.0000
g_1	-	-	-	0.1326*	0.0175	0.0000
Log Likelihood	-11795.04	-	-	-11788.266	-	-
BIC	23799.2244	-	-	23793.7187	-	-

Notes: The superscripts *, ** and *** denote the level significance at 1%, 5%, and 10%, respectively. $Q_t = (1 - a_1 - b_1)\bar{Q} - g_1\bar{N} + a_1Z_{t-1}Z'_{t-1} + b_1Q_{t-1} + g_1\eta_{t-1}\eta'_{t-1}$ 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 $I[\cdot]$ 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.

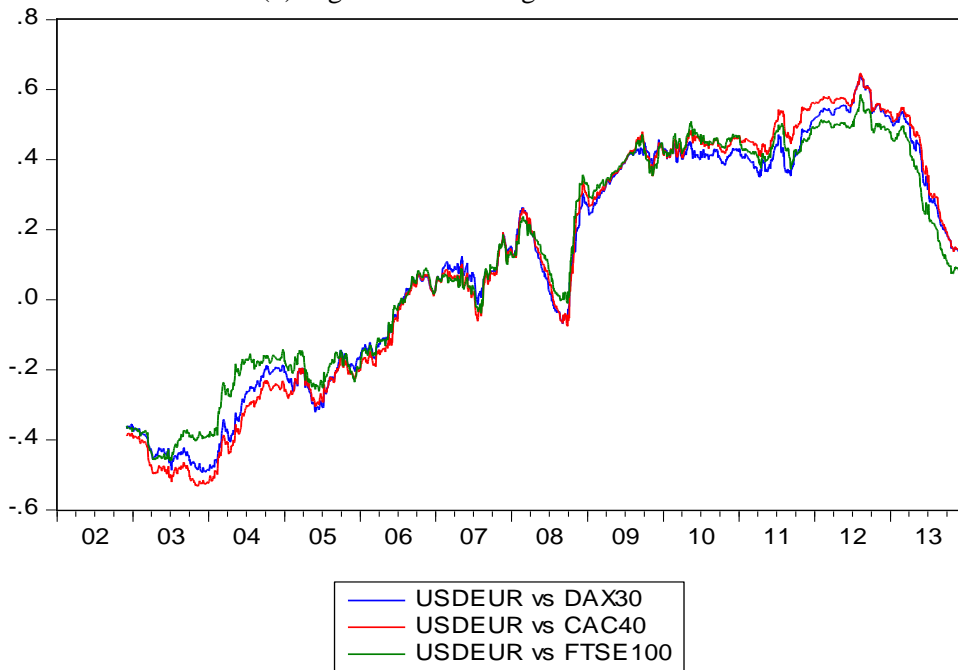
In Fig. 3, we plot the rolling correlations between each pair of exchange rate and stock prices with time spans of four months, eight months, one year, two years and four years, respectively. Interestingly, we find more fluctuations of the rolling correlations in downward directions between each pair, particularly after 2007, regardless of the selected time spans. Moreover, we mainly detect sharp decreases in the correlations between the

USDEUR-DAX30, USDEUR-CAC40 and USDEUR-FTSE100 pairs since 2008 and 2012.

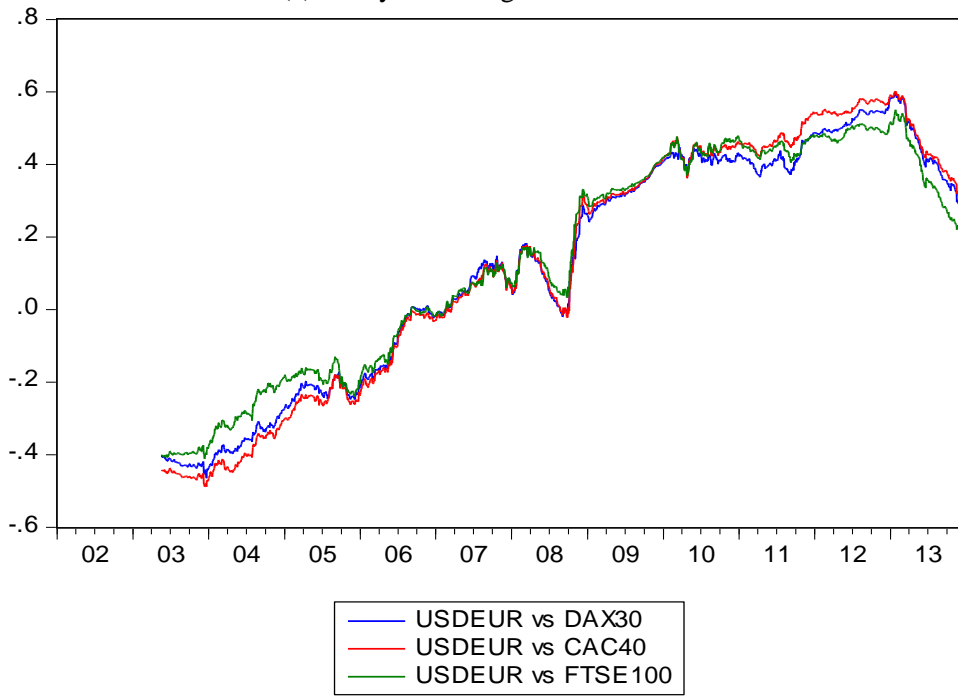
(a) Four-month rolling correlation



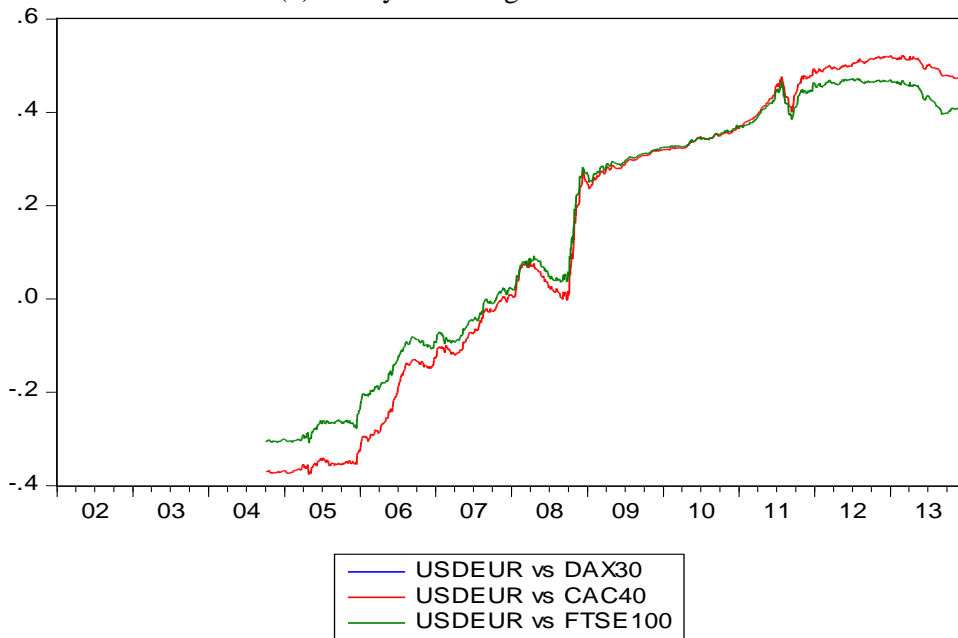
(b) Eight-month rolling correlation



(c) One-year rolling correlation



(d) Two-year rolling correlation



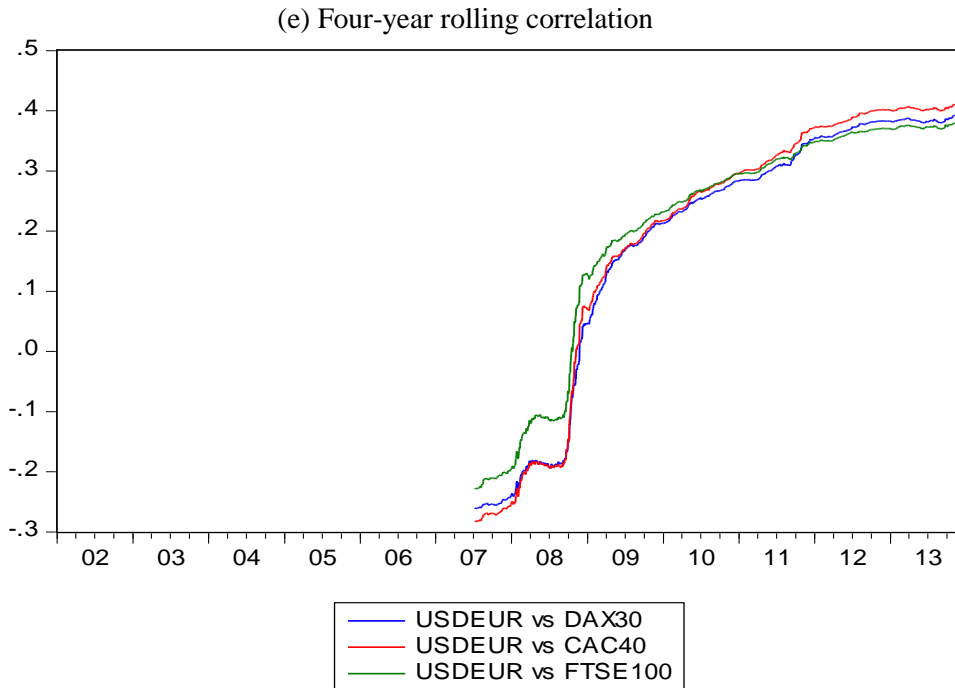
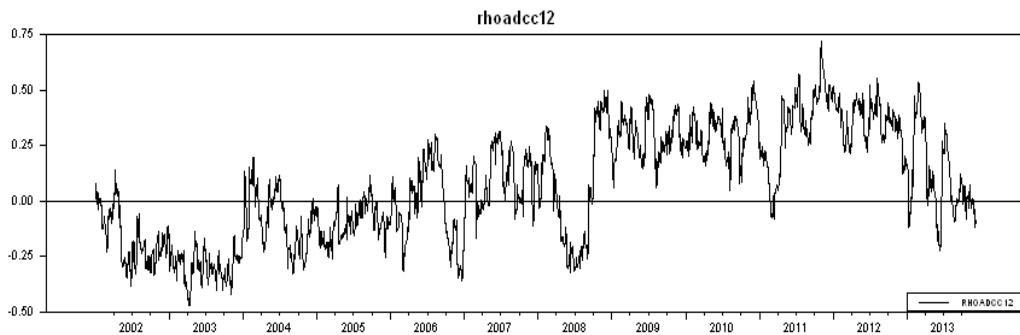


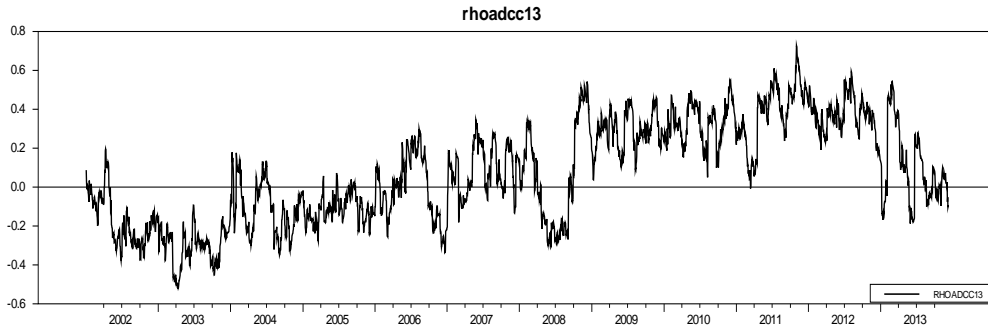
Figure 3: Rolling correlations between exchange rate and stock index pair. (a) Four-month rolling correlation. (b) Eight-month rolling correlation. (c) Two-year rolling correlation. (d) Two-year rolling correlation. (e) Four-year rolling correlation.

Fig. 4 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 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 0.2) before 2007.

(a) The DCC between the USD/EUR and DAX30



(b) The DCC between the USD/EUR and CAC40



(c) The DCC between the USD/EUR and FTSE100

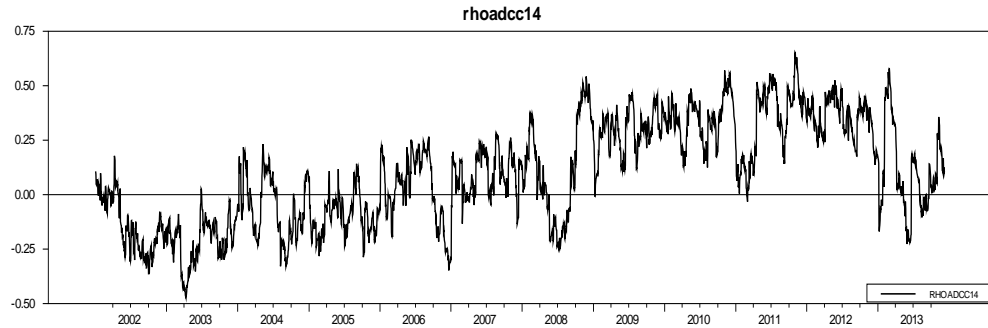


Figure 4: Dynamic conditional correlations between each foreign exchange market and stock market pair. (a) The DCC between the USD/EUR and DAX30. (b) The DCC between the USD/EUR and CAC40. (c) The DCC between the USD/EUR and FTSE100.

4 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 currencies, 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 (see Engle, 2002; Chiang et al., 2007, among others), the dummies are created to the following mean equation:

$$\rho_{ij,t} = \omega_{ij} + \sum_{p=1}^P \varphi_p \rho_{ij,t-p} + \sum_{k=1}^{\lambda} \beta_k \text{dummy}_{k,t} + e_{ij,t} \quad (11)$$

where ω_{ij} is a constant term, $\rho_{ij,t}$ is the pair-wise conditional correlation of the exchange rate and three European stock prices, such that $i, j = \text{USD/EUR, DAX30, CAC40 and FTSE100}$ ($i \neq j$), and $k = 1, \dots, \lambda$ 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 criteria.

Based on the economic approach, $\text{dummy}_{k,t}$ ($k = 1, 2, \dots, 6$) 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:

$$S_{t-1}^- = \begin{cases} 1 & \text{if } \hat{z}_{t-1} < 0 \\ 0 & \text{otherwise} \end{cases} \quad (12)$$

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

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + v_t \quad (13)$$

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:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- z_{t-1} + v_t \quad (14)$$

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:

$$\hat{z}_t^2 = \phi_0 + \phi_1 S_{t-1}^- + \phi_2 S_{t-1}^- z_{t-1} + \phi_3 S_{t-1}^+ z_{t-1} + v_t \quad (15)$$

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 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 (15), which will asymptotically follow a χ^2 distribution with 3 degrees of freedom under the null hypothesis of no asymmetric effects.

Table 5: Tests for sign and size bias for dynamic conditional correlation series.

variable	$\rho_{USDEUR,DAX30}$			$\rho_{USDEUR,CAC40}$			$\rho_{USDEUR,FTSE100}$		
	Coeff	Std.Error	Signif	Coeff	Std.Error	Signif	Coeff	Std.Error	Signif
ϕ_0	0.9711*	0.0706	0.0000	0.7103*	0.0738	0.0000	0.9487*	0.1034	0.0000
ϕ_1	0.095	0.1028	0.3552	0.3626*	0.1072	0.0007	0.0042	0.1325	0.9745
ϕ_2	0.0792	0.0754	0.2933	0.0576	0.0781	0.4606	-0.0587	0.0823	0.4757
ϕ_3	0.0156	0.0709	0.8256	0.2832*	0.0735	0.0001	0.0383	0.1041	0.7130
$\chi^2(3)$	1.1743	—	0.7591	16.5913*	—	0.0008	1.3849	—	0.7090

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

Table 5 reports the results of Engle-Ng tests. As shown in the table, the $\chi^2(3)$ joint test statistics demonstrates a very rejection of the null of no asymmetries for $\rho_{USDEUR,CAC40}$ series and the acceptance of the null hypothesis of no asymmetries for $\rho_{USDEUR,DAX30}$ and $\rho_{USDEUR,FTSE100}$. The results overall would thus suggest motivation for estimating symmetric and asymmetric GARCH volatility models, respectively, for these particular series. Furthermore, the conditional variance equation of the $\rho_{USDEUR,CAC40}$ series is assumed to follow an asymmetric GARCH specification under a student distributed innovations. In our analysis, we choose the student-t-EGARCH(1,1) model (Nelson.,1991) including the dummy variables identified by the economic approach:

$$\ln(h_{ij,t}) = A_0 + A_1 \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right] + B_1 \ln(h_{ij,t-1}) + D_1 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \sum_{k=1}^{\lambda} d_k \text{dummy}_{k,t} \quad (16)$$

According to Eqs. (11) and (16), 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 currencies. 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.

The estimation results of both student-t-AR(1)-GARCH(1,1) and student-t-AR(1)-EGARCH(1,1) models are displayed in Table 6. The constant terms ω_{ij} and the autoregressive term (ϕ_1) are both statistically significant for all DCCs, with the latter taking values close to unity, indicating a strong persistence in the conditional correlations among the examined currencies.

During the phases of global financial and European sovereign debt crises, the results of the mean equation identify a pattern of significant decline in linkages between USDEUR,

DAX30 and USDEUR, FTSE100 currencies. Specifically, the dummy coefficient (β_1) for the phase 1 of the global financial crisis is positive and significantly different from that of the pre-crisis period for only the pair of USDEUR-DAX30 and USDEUR-FTSE100. This evidence suggests that the DCCs between USDEUR and DAX30 and FTSE100 stock prices are increased during phase 1, supporting the existence of a difference in the vulnerability of the currencies. One possible explanation is that the European exchange rate, the Germany and United Kingdom indexes were hit harder at the beginning of the global financial crisis due to the strong financial and economic among European countries and USA (the origin of the crisis). At the phase 2 of the GFC, the dummy coefficient (β_2) is positive and no statistically significant for only the pair of currencies and stock prices, supporting a decrease in DCCs. This suggests that the relationship among exchange rate and stock prices is actually decreased during this phase. This finding can be regarded as a “currency contagion effect”. Both currencies seem to be substantially influenced by USD due to US sharp financial market deterioration. During the phase 3 of macroeconomic deterioration, positive and statistically significant dummy coefficient (β_3) exist for only the pair of currencies, implying an increase of DCCs.

Table 6: 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.

Variable	$\rho_{USDEUR,DAX30}$		$\rho_{USDEUR,CAC40}$		$\rho_{USDEUR,FTSE100}$	
	Coeff	signif	Coeff	signif	Coeff	signif
Mean Equation						
ω_{ij}	-0.0037*	0.0000	-0.0021*	0.0000	-0.0019*	0.0000
φ_1	0.9735*	0.0000	0.9818*	0.0000	0.9784*	0.0000
β_1	0.0026*	0.0214	0.0009	0.3605	0.0018*	0.0000
β_2	0.0018	0.3356	0.0013	0.5933	0.0025	0.1048
β_3	0.0065*	0.0220	0.0041**	0.0738	0.0056*	0.0075
β_4	0.0042**	0.0352	0.0030	0.0508	0.0036*	0.0017
β_5	0.0018	0.5322	0.002	0.1614	0.0031*	0.0086
β_6	0.0145*	0.0000	0.0018*	0.0008	0.0026*	0.0000
Variance Equation						
A_0	0.0003*	0.0000	0.0102*	0.0000	0.1389*	0.0000
A_1	-0.3095*	0.0000	0.1016*	0.0000	-3.0044*	0.0000
B_1	1.0020*	0.0000	0.4864*	0.0000	0.5409*	0.0000
D_1	-	-	0.0056*	0.0000	-	-
d_1	-0.0002*	0.0000	0.0729*	0.0000	0.0835*	0.0000
d_2	0.0028*	0.0000	0.0686	0.1959	-0.0434*	0.0000
d_3	-0.0035*	0.0000	0.0364	0.659	0.1989*	0.0000
d_4	-0.0002*	0.0000	0.0565	0.2845	0.0536*	0.0000
d_5	0.0109*	0.0000	0.025	0.744	0.0467*	0.0000
d_6	-0.0042*	0.0000	-0.0614*	0.0048	0.0525*	0.0000
v	2.0015*	0.0000	2.0004*	0.0000	2.0013*	0.0000
Diagnostics						
$LB(20)$	23.4856	0.2166	22.4579	0.2621	18.5743	0.4844
$LB^2(20)$	12.7237	0.8077	11.6071	0.8668	10.0822	0.9291

Notes: Estimates are based on mean Eq. (13) and variance Eq. (18) and Eq. (19) in the text. φ_p is the coefficient of the pairwise conditional correlation (ρ_{t-1}) with 1 lag among currencies. 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.

At the phase 4 of stabilization and tentative signs of recovery, only the pair of currencies exhibit positive and statistically significant dummy coefficients (β_4), indicating existence of a “currency contagion effect” during this phase and suggesting that both exchange rate and stock prices seem to be substantially influenced by USD due to US macroeconomic deterioration.

The first phase of European sovereign debt crisis exhibits no significantly positive dummy coefficients (β_5) for only the pair of USDEUR-FTSE100. 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. During the last phase of European sovereign debt crisis, significantly positive dummy coefficients (β_6) correspond to the pairs of currencies. Finally, the estimates of the variance Eq. (18) are reported in Table 6. The dummy coefficients d_2 and d_5 for USDEUR-DAX30 are positive and statistically significant across several phases of the two crises. This finding 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. Nevertheless, the dummy coefficients d_1, d_3, d_4 and d_6 for USDEUR-DAX30 are positive and statistically significant. This 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 crises.

5 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 European stock markets using 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.

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 comovements. The conditional correlation among the USD/EUR and European stock index exhibits higher dependency when it is driven by negative innovations to changes than it is by positive innovations. Moreover, the stock market correlations become more volatile during the global financial crisis.

The empirical analysis of the pattern of the time-varying correlation coefficients, during the major crisis periods, provides evidence in favor of contagion effects due to herding behavior

in European stock markets and exchange rate. 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 stock markets. Indeed, the high correlation coefficients, during crisis 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 an 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 European 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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