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Exchange Return Co-movements and Volatility Spillovers Before and After the Introduction of Euro

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Abstract

This paper examines co-movements and volatility spillovers in the returns of the euro, the British pound, the Swiss franc and the Japanese yen vis-à-vis the US dollar before and after the introduction of the euro. Based on dynamic correlations, variance decompositions, generalized VAR analysis, and a newly introduced spillover index, the results suggest significant co-movements and volatility spillovers across the four exchange returns, but their extend is, on average, lower in the latter period. Return co-movements and volatility spillovers show large variability though, and are positively associated with extreme economic episodes and, to a lower extend, with appreciations of the US dollar. Moreover, the euro (Deutsche mark) is the dominant currency in volatility transmission with a net volatility spillover of 8% (15%) to all other markets, while the British pound is the dominant net receiver of volatility with a net volatility spillover of -11% (-13%), in the post- (pre-) euro period. The nature of cross-market volatility spillovers is found to be bidirectional though, with the highest volatility spillovers occurring between the European markets. The economic implications of these findings for central bank interventions, international portfolio diversification and currency risk management are then discussed.

Keywords: Exchange returns co-movement, Volatility spillover, Vector autoregression, Variance decomposition, Spillover index, Multivariate GARCH

JEL codes: C32; F31; G15

1. Introduction

The introduction of the euro more than a decade ago, on the January 1st, 1999, when the exchange rates of the participating countries were locked to the euro was, undoubtedly, one of the most important events for the international financial markets.

The euro has, inter alia, shifted the relative importance and nature of interdependencies of the dollar and the other major trading currencies in the global financial markets. Thus, shifts in portfolio weights and hedge ratios can be expected to have taken place into these markets. The euro came into circulation on January 1st, 2002 and since then has subsequently become a serious competitor to the dollar in international usage. According to the Bank for International

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Settlements the euro rapidly became the second most traded currency behind the US dollar in the international exchange markets. The BIS (2010) Triennial Central Bank Survey on Foreign Exchange and Derivative Market Activity in 2010 shows that, in April 2010, the average daily turnover of the euro accounted for 39.1% of all transactions (such as spot and forward transactions and FX swaps), while the US dollar accounted for 84.9%. The Japanese yen, the British Pound and the Swiss franc follow with turnovers of 19%, 12.9% and 6.4%, respectively.[1]

Among others, the purpose of candidate countries joining the euro area and thus adopting its currency, is to reduce transaction costs and eliminate exchange rate uncertainty arriving from own market shocks and possibly for shocks spilling over from other markets (known as the 'heat wave' and 'meteor shower' effects, respectively, named by Engle et al. (1990) who initiated research in this area). In addition, the fact that the euro area is continuously enlarged with new members that will subsequently adopt the euro, there exists the possibility the euro in the future to rival or surpass the US dollar, and become the world's leading international reserve currency (Chinn and Frankel, 2007).

The analysis of such interdependencies and volatility spillovers in major exchange rates, and their evolution over-time is of great importance influencing the decisions of central bank interventions, international trade, risk management and portfolio diversification. Moreover, a formal assessment of the evolution of these relationships during the post-euro period in relation to the pre-euro period will provide insights of the transformation and the changing pace in financial integration.

The literature on co-movements and volatility spillovers among exchange rate series since the introduction of the euro is ample. Inagaki (2007) using residual cross-correlation functions (CCF) investigates volatility spillovers between the British pound and the euro vis-à-vis the US dollar spot exchange rates between 1999 and 2004 and finds unidirectional volatility spillover from the euro to the pound. Nikkinen et al. (2006) offers additional support to Inagaki's result using a VAR framework on currency option data for the British pound, the euro and the Swiss franc between 2001 to 2003. They additionally find that the highest correlations exist between the euro and the franc, and the euro is the dominant currency in volatility transmission. On similar grounds, McMillan and Speight (2010) using the US dollar, the Japanese yen and the British pound vis-à-vis the euro between 2002 and 2006 find that the dollar rate dominates the other two rates in terms of both return and volatility spillovers.

Pérez-Rodrìguez (2006) employs the DCC model of Engle (2002) to examine the interdependencies of daily conditional volatilities of the euro, the pound and the yen against the US dollar over the period 1999-2004. The author finds evidence of significant volatility spillovers between the euro, yen, and the pound, and that correlations are high between the euro and the pound. Under a similar approach, Kitamura (2010), using intra-daily data during April 2 and August 31 2006, finds significant return volatility spillovers of the euro to the pound and the franc, and that the pound and franc are highly integrated to the euro market. Using wavelet analysis, Nikkinen et al. (2011) find that option-implied expectations of the euro, the Japanese yen, and the British pound vis-à-vis the US dollar are closely linked. In addition, volatility of the yen is found to affect the volatilities of the euro and the pound in the short-run, whilst significant feedback effects from the pound volatility expectations to the yen are also evident in the long-run.

Another strand of literature examines the asymmetric responses of higher moments of exchange

[1]The reason % shares exceed 100% is because two currencies are involved in each transaction hence, the sum of the % shares of individual currencies used in the BIS report totals 200%.

rates. For instance, Boero et al. (2011) find different degrees of pairwise co-movements of the euro, the pound and the yen during appreciations and depreciations against the US dollar for the period 1994 to 2007. Wang and Yang (2009) using data between 1996 and 2004, find evidence of asymmetric volatility in the Australian dollar (AUD), British pound (GBP) and the Japanese yen (JPN) against the USD exchange rates. Specifically, a depreciation against the USD leads to significantly greater volatility than an appreciation for the AUD and the GBP, whilst the opposite not being true for JPY.

However, little is known about return co-movements and volatility spillovers among major exchange rates in relation to the pre-euro period. One of the exceptions is the study of Boero et al. (2011), which investigates the bivariate dependence structure of the Deutsche mark (euro after 1999), the British pound, the Swiss franc and the Japanese yen vis-à-vis the US dollar before and after the introduction of the euro. Based on copula and non-parametric plots the authors find that, in addition to the results reported above, co-movements of the pound and the euro increase in the post-euro period compared to the pre-euro and its transition period, while co-movements of the euro and the franc remain relatively unchanged over time.

The aim of this study is to fill in this gap in the literature by examining the extend and the nature of interdependencies and volatility spillovers of major exchange returns in the post-euro period, and statistically assessing their differences with the pre-euro period, the latter being the key contribution of this study. The second contribution of this study is the application of the newly generalized version of the spillover index of Diebold and Yilmaz (2012), which overcomes common pitfalls found in the identification scheme of variance decompositions, as in the originally introduced spillover index of Diebold and Yilmaz (2009). The results of the generalized version of the spillover index along with those from multivariate GARCH methodology, generalized vector autoregressions (VAR) and variance decompositions can be summarized as follows. There is evidence of significant co-movements and volatility spillovers across the four exchange returns, but in the post-euro their magnitude is, on average, significantly lower compared to the pre-euro period. Nevertheless, return co-movements and volatility spillovers are positively associated with extreme economic episodes, such as stock market crashes, currency and debt crises, and US recessions, and, to a lower extend, with depreciations against the US dollar. Moreover, the euro (Deutsche mark) is the dominant currency in volatility transmission with a net volatility spillover of 8% (15%) to all other markets, while the British pound is the dominant net receiver of volatility with a net volatility spillover of -11% (-13%), in the post- (pre-) euro period. The nature of cross-market volatility spillovers is found to be bidirectional though, with the highest volatility spillovers occurring between the European markets. The economic implications of these results for central bank interventions, international portfolio diversification and currency risk management are then discussed.

The remainder of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the empirical results and discusses their implications, and section 4 concludes.

2. Data and methodology

The data employed in this study consist of daily spot exchange rates of the euro (EUR), British pound (GBP), Japanese yen (JPY) and the Swiss franc (CHF) against the US dollar over the period from January 6th, 1986 to December 30th, 2011.[2] The series were obtained from the Bank of England online database. The four currencies chosen are among the most traded currencies as defined by the daily trading volume and the size of the economy in the BIS (2010) report. The data were split into two sub-periods; the periods i) prior to and ii) after the introduction of euro. Specifically, the date of separation is the January 1, 1999, the date on which exchange rates were irrevocably fixed against the euro. The reason the sample period starts on January 1986 and ends on December 2011 is to give almost equal numbers of observations in the pre- and the post- euro period (specifically 3286 and 3284 daily observations, respectively). In the pre-euro period analysis, the euro spot rate is replaced by the Deutsche mark rate.[3]

Following previous work on spot exchange rates data, where the spot rates are generally non-stationary, I focus on daily exchange rate returns defined as: $r_t = ln(y_t) - ln(y_{t-1})$, where y_t is the spot exchange rate at time t, with $t = 1, 2, ..., T$, and ln the natural logarithm. According to the results of the Augmented Dickey-Fuller (ADF) test-statistic reported in Table 1, the null hypothesis of a unit root in the first logarithmic differences of each exchange rates series is rejected.

To examine the time-varying nature and the interrelations in return co-movements I employ the Dynamic Conditional Correlation (DCC) model proposed by Engle (2002).[4] The DCC model uses a two-step procedure. In the first step, the individual conditional variances are specified as univariate GARCH processes and in the second step the standardized residuals from the first step are used to construct the conditional correlation matrix. This method overcomes certain numerical difficulties often arising in estimating multivariate GARCH models (such as the estimation of many parameters simultaneously, which might not ensure positive definiteness of the covariance matrix), and it also enables the estimation of time-varying volatilities, covariances and correlations.

The DCC model of Engle (2002) is defined as:

$$r_t = \mu_t(\theta) + \epsilon_t, \quad \text{where} \quad \epsilon_t|\Omega_{t-1} \sim N(0, H_t) \tag{1}$$

$$\epsilon_t = H_t^{1/2} u_t, \quad \text{where} \quad u_t \sim N(0, I) \tag{2}$$

$$H_t = D_t R_t D_t \tag{3}$$

where $r_t = (r_{it}, ..., r_{Nt})'$ is a $Nx1$ vector of exchange returns (specifically the euro, British pound, Japanese yen and the Swiss franc returns, thus N=4), $\mu_t(\theta) = (\mu_{it}, ..., \mu_{Nt})'$ is the conditional $4x1$ mean vector of r_t, H_t is the conditional covariance matrix, $D_t = diag(h_{iit}^{1/2}, ..., h_{NNt}^{1/2})'$ is a diagonal matrix of square root conditional variances, where h_{iit} can be defined as any univariate GARCH-type model, and R_t is the $tx\left(\frac{N(N-1)}{2}\right)$ matrix containing the time-varying conditional correlations defined as:

$$R_t = diag(q_{ii,t}^{-1/2}, ..., q_{NN,t}^{-1/2}) Q_t diag(q_{ii,t}^{-1/2}, ..., q_{NN,t}^{-1/2}) \quad \text{or} \quad \rho_{ij,t} = \rho_{ji,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \tag{4}$$

[2]The exchange rate is defined as one unit of domestic currency (USD) in terms of foreign currency (e.g. EUR). Thus, an increase in the exchange rate (EUR/USD) denotes an appreciation of the domestic currency (USD).

[3]A similar exchange rate replacement and date separation is used in Boero et al. (2011). Moreover, having artificial data for the euro (obtained from the Bank of England online database) over the first sub-period, it is found that the unconditional correlation between the euro and the Deutsche mark is 0.987 supporting the idea of replacing the euro with the Deutsche mark in the former period.

[4]A similar specification of the DCC model has been proposed by Tse and Tsui (2002).

where $Q_t = (q_{ij,t})$ is a NxN symmetric positive definite matrix given by:

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1} u_{t-1}^{'} + \beta Q_{t-1} \tag{5}$$

where $u_t = (u_{1t}, u_{2t}...u_{Nt})'$ is the $Nx1$ vector of standardized residuals, $\bar{Q}$ is the NxN unconditional variance matrix of u_t, and α and β are nonnegative scalar parameters satisfying $\alpha + \beta < 1$.

The DCC model is estimated using the Quasi-Maximum Likelihood (QML) estimator under a multivariate Student distribution (see Harvey et al., 1992; Fiorentini et al., 2003). The multivariate Student distribution is applied as the normality assumption of the innovations is rejected for each exchange return series.

To examine spillovers in the volatility of the four exchange returns, I apply generalized vector autoregressive (VAR) methodolody, variance decomposition and the generalized version of the spillover index in Diebold and Yilmaz (2012), originally proposed by Diebold and Yilmaz (2009). The generalized version overcomes the shortcomings of potentially order-dependent results due to Cholesky factor orthogonalization in Diebold and Yilmaz (2009).

Variance decomposition analysis is very useful, as it allows to examine how much of the forecast error variance of each variable can be explained by exogenous shocks to the other variables. Put differently, they can provide answers to the question such as: What fraction of the H-step ahead forecast error variance in variables y_{it}, for $i = 1, 2, \ldots, N$, is due to shocks to the other, y_{jt}, variables, for $j = 1, 2, \ldots, N$, such that $i \neq j$? The direction of such spillovers denote cross-variance shares as discussed below. The own-variance shares are indicated by the fraction of the H-step ahead forecast error variances in forecasting y_{it} due to shocks in y_{jt}, such that $i = j$.

Having calculated variance decompositions, the generalized version of the spillover index of Diebold and Yilmaz (2012) is then constructed. The spillover index, which aggregates the information provided by variance decompositions into a single value, captures the degree of spillovers within the markets examined. Essentially, the spillover index calculates the degree of cross-markets spillovers as captured by the share of cross-market error variance in the variance decomposition relative to the total error variance of the markets examined.

To simplify illustration of the spillover index construction, and following the discussion of Diebold and Yilmaz (2012) assume the following p-order 4-variable VAR

$$y_t = \sum_{i=1}^{p} \Theta_i y_{t-1} + \varepsilon_t \tag{6}$$

where $y_t = (y_{1t}, y_{2t}, y_{3t}, y_{4t})$ is a vector of four endogenous variables, Θ is a 4×4 parameter matrix and $\varepsilon_t \sim (0, \Sigma)$ is vector of independently and identically distributed disturbances. Then, the moving average representation is $y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-1}$, where the 4×4 coefficient matrices A_i obey the recursion $A_i = \Theta_1 A_{i-1} + \Theta_2 A_{i-2} + \ldots + \Theta_p A_{i-p}$, with A_0 the 4×4 identity matrix and $A_i = 0$ for $i < 0$.

Then, variance decomposition transformation of the moving average coefficients can help us understand the dynamics of the system. The results of such dynamics will depend on whether or not VAR innovations are contemporaneously correlated, and the identification scheme applied. Since VAR innovations are generally contemporaneously correlated, identification schemes such as based on Cholesky factorization achieve orthogonality, but variance decompositions results will then depend on variables' ordering.

To overcome this shortcoming, the generalized VAR framework of Koop et al. (1996) and Pesaran and Shin (1998) is used, which produces variance decompositions invariant to the variable ordering. According to this framework, the H-step-ahead forecast error variance decomposition is

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

where Σ is the variance matrix of the error vector ε, σ_{ii} the standard deviation of the error term for the ith equation and e_i the selection vector with the one as the ith elements and zeros otherwise. Then, each entry of the variance decomposition matrix is normalized, so that each row in the variance decomposition table to equal to one, as follows

$$\tilde{\phi}_{ij}^{g}(H) = \frac{\phi_{ij}^{g}(H)}{\sum_{j=1}^{N} \phi_{ij}^{g}(H)} \tag{8}$$

with $\sum_{j=1}^{N} \tilde{\phi}_{ij}^{g}(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{\phi}_{ij}^{g}(H) = N$ by construction. Using these results, the total volatility spillover index is constructed as

$$S^{g}(H) = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \phi_{ij}^{g}(H)} * 100 = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\phi}_{ij}^{g}(H)}{N} * 100 \tag{9}$$

and determines the contribution of spillovers of volatility shocks across all variables to the total forecast error variance.

The directional spillovers across variables can also be defined. Specifically, the directional spillovers received by variable i from all other variables j are defined as

$$S_{i \leftarrow j}^{g}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\phi}_{ij}^{g}(H)}{\sum_{j=1}^{N} \phi_{ij}^{g}(H)} * 100 \tag{10}$$

and the directional spillovers transmitted by variable i to all other variables j as

$$S_{i \rightarrow j}^{g}(H) = \frac{\sum_{j=1, j\neq i}^{N} \tilde{\phi}_{ji}^{g}(H)}{\sum_{j=1}^{N} \phi_{ji}^{g}(H)} * 100. \tag{11}$$

Finally, subtracting Eq. (10) from Eq. (11) we obtain the net spillovers as

$$S_{i}^{g} = S_{i \rightarrow j}^{g}(H) - S_{i \leftarrow j}^{g}(H), \tag{12}$$

from variable i to all other variables j.

3. Empirical results

3.1. Descriptive statistics

Table 1 presents descriptive statistics of the EUR, the GBP, the JPY and the CHF returns series in the pre- and the post- euro period.

[insert Table 1 around here]

In each sample period, GBP's standard deviation is the smallest, while CHF's the largest. In addition, the unconditional standard deviations of each return have declined, on average, since the introduction of the euro. The excess kurtosis coefficient is significantly greater than zero indicating non-normality of returns. However, the excess kurtosis coefficient increased in the case of the European currencies, while declined for the yen since the launch of the euro. According to the Jarque-Bera statistic all exchange returns are, as expected, not normally distributed, as the null hypothesis of normally distributed returns is persuasively rejected.

Moreover, Table 1 reports the Ljung-Box Q and Q^2 statistics, which test the null hypothesis of no serial correlation in returns and squared returns, respectively, against the alternative that are serially correlated. According to the Q statistic results, only the JPY in the pre-euro period and the EUR, JPY and the CHF in the post-euro period can be characterized as random walk processes. However, the Q^2 statistic in the squared returns is significant for each return series indicating strong non-linear dependencies. This is also supported by Engle's ARCH-LM statistic. The null hypothesis of no ARCH effects is rejected for each series at 5% level of significance.[5]

Summing up, the returns series are characterized by non-randomness and the presence of ARCH effects, and the squared returns by the presence of higher order serial correlation and non-linear dependency. The findings of higher order serial correlation, and non-linear dependency support the decision to model exchange rate volatility through a GARCH-type process.

Figure 1 plots the evolution of the exchange rates over time.[6] We observe that exchange rates move closely together and especially the two 'European' currencies, namely the euro and the Swiss franc. This feature is evident in both the pre- and the post- euro period. Since the beginning of 1986 until early in 1991, all four currencies appreciated against the dollar with a depreciation period between 1988 and mid 1989. After 1991, a sharp depreciation took place till mid 1991 followed by an appreciation period, with another couple of sharp depreciations in mid 1992 and 1993, until the first quarter of 1995. Since then, the mark, the yen and the franc depreciated against the dollar until the introduction of the euro, while the pound remained relatively stable. Since the launch of the euro, the presence of co-movements in all four currencies is again highly evident apart from the yen between mid 1999 until 2002, and mid 2005 until the end of 2009. In addition, co-movement between the pound and the rest of the currencies declined from 2004 onwards.

[insert Figure 1 around here]

Figure 2 which plots the exchange returns in both periods shows the feature of volatility clustering. That is, periods of relative tranquillity followed by periods of more turbulent volatility.

[insert Figure 2 around here]

Moreover, in Table 1, I present the unconditional sample correlations between these exchange returns. These correlations indicate that market expectations of exchange returns are contemporaneously and positively correlated across the four major currencies' returns. They range from 0.127 for the yen-pound correlation to 0.933 for the mark-franc correlation. In addition, among all six unconditional pairwise return correlations, the euro(mark)-franc are the greatest in both periods. The euro(mark)-pound, franc-pound, franc-yen, euro(mark)-yen and the pound-yen return

[5] For the Swiss franc the null hypothesis of no ARCH effects is rejected at 10% level of significance.

[6] Exchange rates are scaled by their means in Figure 1.

correlations capture the second, third, fourth, fifth and sixth place, respectively. The fact that the observed correlations are higher between the European currencies is in line with the phenomenon of intra-regional rather than inter-regional currency contagion (e.g. see Glick and Rose, 1998). A representative example of such intra-regional currency contagion is the Asian currency crisis in 1997. Another interesting feature is that all pairwise correlations have declined, on average, in the post-euro period compared to the pre-euro period, indicating that returns became less closely tied, on average, since the launch of the euro.

3.2. Exchange return co-movements

In this section, I present the results of the time-varying measure of correlations obtained from the DCC model of Engle (2002).

Table 2 presents the empirical results of the DCC model for the pre- and the post- euro period. An AR(3)-DCC-MGARCH(1,1) and a random walk DCC-MGARCH(1,1) model were chosen in order to remove any serial correlation in returns in the pre- and the post- euro, respectively.[7]

[insert Table 2 around here]

The estimated conditional correlation parameters ($\hat{\rho}_{ij,t}$) on Table 2 report evidence of highly significant dynamic conditional correlations in the both the pre- and the post-euro period. As expected, the largest conditional correlations are between returns belonging to countries geographically closer to each other, namely the euro (mark), the franc and the pound. The strongest in magnitude co-movements occur between the euro-franc, the euro-pound and the franc-pound returns in both periods while the lowest between the yen-pound, yen-eur and the yen-franc.[8] This result is again in line with the literature that currency contagions are of intra-regional rather than inter-regional nature see (Glick and Rose, 1998).

In both periods, the DCC model seems to be very well specified, as the estimates of the DCC parameters, α and β, are always statistically significant indicating that the second moments of exchange returns are indeed time-varying; a feature documented in many studies (see, for instance, Dias and Embrechts, 2010).[9]

The most interesting feature of Table 2 is that, on average, the magnitude of co-movements is lower in the post-euro period compared to the pre-euro period. These results are in contrast to those in Boero et al. (2011). For instance, in Boero et al. (2011), co-movements between the EUR and the GBP returns increase after the introduction of the euro compared to period before the euro while, I find the opposite. However, the explanation behind this contradiction is the difference in the pre- and the post- euro period sample size used.[10]

[7] The Akaike Information Criterion (AIC), the Schwarz Bayesian Criterion (SBC) and overfitting approaches were used to determine the optimal lag structure of exchange returns in the conditional mean equation.

[8] This is in line, among others, with Nikkinen et al. (2006) and Boero et al. (2011) who found that the highest correlations exist between the euro and the franc.

[9] In addition, the two tests for constant correlations of Tse (2000) and Engle and Sheppard (2001) rejected the null of no constant correlations at 5% level of significance. In the pre-euro period the value of the Tse (2000) and Engle and Sheppard (2001) tests were 73.88 and 69.23 with p-values of [0.00] and [0.00], respectively, whilst 76.35 and 123.36 with [0.00] and [0.00] p-values, respectively, in the post-euro period.

[10] Restricting the sample size to match that in Boero et al. (2011), I also find that dynamic correlations of the EUR and the GBP increased since the introduction of the euro from 0.59 during Jan. 1994 - Dec. 1998, to 0.61 during Jan. 1999 - Feb. 2002, and finally to 0.73 during Mar. 2002 - Nov. 2007.

To statistically assess the significance of the decline in magnitude of return co-movements reported above, I apply a standard Z-test statistic (Morrison, 1983).[11] The null hypothesis that dynamic correlations are, on average, not lower in magnitude in the post-euro period compared to the pre-euro period is rejected for each pairwise conditional correlation apart from the CHFEUR correlations at 1% level of significance. The Z-Statistics (p-values) for the GBPEUR, JPYEUR, JPYGBP, CHFGBP and CHFJPY correlations are -9.93 ([0.00]), -12.25 ([0.00]), -11.65 ([0.00]), -9.44 ([0.00]) and -13.01 ([0.00]), respectively, while -1.21 ([0.24]) for the CHFEUR correlation. The fact that co-movements between the euro (mark) and the franc have not significantly declined, on average, in the post-euro period is in line with the results in Boero et al. (2011) and for a more extended sample.

While the estimated conditional correlation parameters of the DCC model and the results of the Z-test provide a useful summary of the 'average' behavior of return co-movements, they are likely to miss important economic events that occurred within each of our sample periods. Figure 3 shows the evolution of conditional correlations obtained from the DCC model in both periods. One can clearly observe that correlations do not remain constant over time in both the pre- and the post- euro periods, as correlations range between -0.221 to 0.978 and -0.459 to 0.983, respectively.

[insert Figure 3 around here]

Specifically, in the pre-euro period, correlation coefficients of each return series are higher between 1987 and 1990, 1991 and 1992, in 1995 and in 1997-1998. Coupled with the fact that conditional variances and covariances are higher during the same periods,[12] is in agreement with empirical studies of the relationships between currency markets for which correlations (or even spillovers that I examine below) tend to increase during periods of extreme episodes such as political turmoil, and currency and debt crises. The large increases in conditional variances, covariances and correlations, particularly for the pre-euro period coincide, hence, are possibly associated with the cut of the discount rate from 6% to 5.5% by Federal Reserve on the 14 April 1991, with the political turmoil in Russia (where news of a coup in the Soviet Union against president Gorbachev arrived on 19 August 1991), with the ERM crisis in 1992-93 (with the pound being suspended on 16 September 1992), the Mexican-Peso crisis in 1994-1995 and the Asian crisis in 1997-1998 (Lobo, 2002). The same applies in the post-euro period. Correlations are greater between the end of 2001 and the mid of 2003 (early 2000s recession in US and EU), at the beginning of 2004 (Argentina's energy crisis) till the end of 2006, and from the fall of 2008 (global financial crisis) till the mid of 2011 (Eurozone debt crises), which coincide with periods of increased uncertainty.

Having illustrated how major exchange returns co-move, a natural question that arises is what explains such co-movements. Are co-movements, for instance, related to appreciations or depreciations of the US dollar and/or to periods of downturn in economic activity?[13] To answer that, I

[11]The Z-test statistic for the null hypothesis of no decrease in correlations is defined as: $T = \frac{Z_1 - Z_0}{\sqrt{\frac{1}{N_0-3} + \frac{1}{N_1-3}}}$, where $Z_0 = \frac{1}{2} \ln\left(\frac{1+\tilde{\rho}_0}{11\tilde{\rho}_0}\right)$, $Z_1 = \frac{1}{2} \ln\left(\frac{1+\tilde{\rho}_1}{11\tilde{\rho}_1}\right)$, $\tilde{\rho}_0$ and $\tilde{\rho}_1$ refer to pre-euro and post-euro correlations, respectively, $N_0 = 3286$ and $N_1 = 3284$. This test statistic is approximately normally distributed and is fairly robust to the non-normality of correlation coefficients.

[12]Those two graphs are not included but are available upon request.

[13]Even though a huge literature exists on the effects of fundamentals on returns and their co-movements, they are not taken into account in this paper, since such data on daily frequencies do not exist. However, the investigation of fundamentals on dynamic correlations of returns using lower frequency data might serve an avenue for future research.

estimate panel regressions of the form

$$\begin{aligned}\Delta\rho_{ij,t} &= \mu_{ij} + \beta_1 Trend + \beta_2 Dep_{ij,t} + \beta_3 App_{ij,t} + \beta_4 Rec_{ij,t} \\ &\quad + \beta_5 Dep_{ij,t} \times Rec_{ij,t} + \beta_6 App_{ij,t} \times Rec_{ij,t} + \varepsilon_{ij,t} \end{aligned} \tag{13}$$

where $\Delta\rho_{ij,t}$ is the first difference of the estimated dynamic conditional correlation between return i and j, μ_{ij} are country-specific effects and $Trend$ is a linear trend. To check for possible asymmetric influence of depreciations and appreciations of the US dollar on correlations I include two dummy variables: $Dep_{ij,t}$, which is equal to 1 if both currencies i and j depreciate jointly against the US dollar and 0 otherwise, and $App_{ij,t}$, which is equal to 1 if both currencies i and j appreciate jointly against the US dollar and 0 otherwise. To check whether correlations increase during crises, I include the dummy variable $Rec_{ij,t}$ defined as $Rec_{ij,t} = 1$ if the US economy was in recession and $Rec_{ij,t} = 0$ otherwise.[14] Finally, I interact the US recession dummy variable with $Dep_{ij,t}$ and $App_{ij,t}$ to test weather asymmetries exist during downturns of economic activity.

Table 3 presents these results. We can observe that, in the pre-euro period, no asymmetric influence of joint depreciations or appreciations against the US dollar on dynamic correlations exist on average, while, in the post-euro period, joint depreciations against the USD significantly increase dynamic correlations indicating asymmetric responses of correlation during depreciations against the USD. However, appreciations against the USD decrease, albeit insignificantly, correlations in the post-euro period. Turning to the results for the dummy variable indicating US recessions, which are reported in Columns (II)-(IV), confirms that correlations increase during downturns of US economic activity, as $Rec_{ij,t}$ enters significantly positive, regardless of the exact specification. Even tough depreciations against the USD do not exert influence on correlations in the pre-euro period, they significantly increase correlations during US recessions (Column (III)) indicating asymmetric influence during downturns. The time trend turns out to be insignificantly negative in each period indicating insignificant decline in return co-movements within each period.

[insert Table 3 around here]

These results are of great importance for central banks, among others, who want to achieve, for instance, a certain level of depreciation/appreciation against more than one foreign currency simultaneously. Moreover, knowing that a depreciation of the yen against the US dollar is likely to cause a depreciation of the euro against the US dollar, then such information is useful in deducing how the changes in the competitiveness of Japan against the US would affect the competitiveness of the Euro area against the US. The implications of the preceding results are also important for international currency portfolio diversification and risk management which I further explore in section 3.4.

3.3. Volatility spillovers

In this section, I present the volatility spillovers results based on the generalized VAR framework, variance decompositions and the generalized spillover index of Diebold and Yilmaz (2012), in the each period. The estimated conditional volatilities parameters of the four return series obtained from the DCC model in the previous section are used as the y_{it} variables in Eq. (6), where $i = EUR(DM)CV, GBPCV, CHFCV, JPYCV$ (where CV denotes conditional volatility).

[14] US recession dates were obtained from the National Bureau for Economic Research Business Cycle Dating Committee.

The results of the degree and direction of volatility spillovers within and across the four exchange markets are shows in Table 4.

[insert Table 4 around here]

Before discussing the results though, it is necessary to explain the rows and the columns of Table 4. The ijth entry in this table is the estimated contribution *to* the forecast error variance of volatility i coming *from* innovations to volatility j. Thus, the diagonal elements ($i = j$) measure own-market volatility spillovers, while the off-diagonal elements ($i \neq j$) capture cross-market volatility spillovers within two markets. In addition, the summation of each off-diagonal columns (labeled 'Contributions to others') or rows (labeled 'Contributions from others') gives the total 'to' and 'from' volatility spillovers in each market, respectively, in each panel. The difference between each off-diagonal column sum with each off-diagonal row sum, respectively, gives the net volatility spillover from market i to all other markets j. The total volatility spillover index, given in the lower right corner of each panel in Table 4, is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or row sum including diagonals), expressed in percentage.

Several interesting results emerge from Table 4. First, own-market volatility spillovers explain the highest share of forecast error volatility, as the diagonal elements receive higher values compared to the off-diagonals elements. However, own-market volatility spillovers have increased in the post-euro period indicating increased volatility persistence within each market since the launch of the euro. Second, according to the off-diagonal elements, I observe large cross-market volatility spillovers among all markets in the post-euro period and mostly among the European markets in the pre-euro period indicating increased influence of (to) the yen volatility to (from) the european markets' volatility since the launch of the euro.

Third, the euro (mark) is the dominant currency in volatility transmission as, according to the 'contribution to the others' row, gross directional volatility spillovers to others are the highest in the euro (mark) market in both periods, while in the yen and the franc markets are the lowest in the pre- and post- euro period, respectively. The former result is in line with the result in Nikkinen et al. (2006), Kitamura (2010) and McMillan and Speight (2010), who find that the euro volatility spills over to the pound and the franc volatility. However, in this study the euro (mark) volatility is also affected by the contribution of other markets' volatility indicating bidirectional volatility spillover rather than unidirectional volatility spillovers between the euro (mark) and the other markets. Besides, from the last column of Table 4, we see that volatility spillovers from others are relatively similar, with the euro (mark) ranking, albeit marginally, first. The finding that the euro (mark) is the dominant currency in volatility transmission can also be supported by the net volatility spillovers values, which measure net volatility spillovers from market i to all other markets j, reported in the last column of each panel of Table 4. Specifically, the euro (mark) is the dominant currency in volatility transmission with a net volatility spillover of 8% (15%) to all other markets in the post- (pre-) euro period, while the British pound is the dominant currency in receiving volatility from all other markets with a net volatility spillover of -11% (-13%) in the post- (pre-) euro period. These results are of great importance as, monitoring, for instance, the activity in other financial markets can be a good indicator of future changes in activity in the financial market of interest.

The fact that the direction of volatility spillovers between the euro, the pound, the franc and the yen is bidirectional is in contrast with the results found in Nikkinen et al. (2006) and McMillan and

Speight (2010). There are, however, several explanations for this disagreement, such as alternative data and sample size used, but most importantly, identification schemes and variable ordering when conducting variance decompositions in VARs. For instance, the results in McMillan and Speight (2010) using Cholesky factorization to obtain variance decompositions and construct the volatility spillovers index of Diebold and Yilmaz (2009) can be variable-ordered-dependent as noted by Diebold and Yilmaz (2012). In this paper, I avoid such shortcomings as described above.

Fourth, and most importantly, according to the total volatility spillover index presented at the bottom right corner in each panel of Table 4 and which effectively distils the various directional volatility spillovers into a single index suggests that, within these four markets, volatility spillovers in the post-euro period are, on average, lower compared to the pre-euro period. Specifically, 46% of volatility forecast error variance in all four markets comes from volatility spillovers in the pre-euro period, whilst 31% in the post-euro period.

Nevertheless, having again an average measure of volatility spillovers over such long periods of time, wherein several crises and other key economic events occurred, might obscure valuable secular and cyclical movements in volatility spillovers. To overcome this, I estimate the model in Eq. (6) using 200-day rolling samples, and gauge the magnitude and nature of volatility spillovers through the corresponding time series of the spillover indexes.

Figure 4 presents the time-varying measure of the total volatility spillover index in both periods obtained from estimating volatility spillovers using 200-day rolling samples. Indeed large variability in the total volatility spillover index is observed, but no clear cut evidence of a trend within each period, apart from a gently increasing trend within the post-euro till the end of 2009 and a trend reversal afterwards. In addition, the total volatility spillover index is responsive to economic events, such as stock market crashes, and currency and debt crises in both periods. For instance, volatility spillovers between these four markets reached a peak during the 'Black Monday' of October 19, 1987 in the pre-euro period, and during the global financial and EU debt crises of 2007-2010 since euro's introduction. During other episodes, such as the ERM 1992-93 crisis, the 2000-01 EU and US recessions, and the 2002-03 Iraq crisis, volatility spillovers increased substantially too.

[insert Figure 4 around here]

Even though the total volatility spillover index and its evolution is important, it discards directional information. Such information is contained in the "Contribution to others" row (the sum of which is given by $S^g_{i<-j}(H)$ in Eq. (10)) and the "Contribution from others" column (the sum of which is given by $S^g_{i->j}(H)$ in Eq. (11)) in Table 4. Estimating the above mentioned row and column of Table 4 using 200-day rolling samples we obtain the directional volatility spillovers plotted in Figures 5 and 6. Specifically, Figure 5 presents the directional volatility spillovers from each of the four markets to others (corresponding to the "Contribution to others" row in Table 4), while Figure 6 presents the directional volatility spillovers from the others to each of the four markets (corresponding to the "Contribution from others" column in Table 4) in both periods. According to these figures, the bidirectional nature of volatility spillovers between the euro, the pound, the franc and the yen is further supported in both periods, with directional volatility spillovers from and to the European markets being more pronounced than those from and to the Japanese market. Moreover, directional volatility spillovers from each of the four markets to others are higher than directional volatility spillovers from others to each of the four markets. For instance, directional volatility spillovers from the DM (EUR), the CHF or the GBP market to others reach up to 28%, while directional volatility spillovers from others to the DM (EUR), the CHF or the

GBP market do not exceed the 20% threshold. Moreover, directional spillover vary greatly over time and are responsive to economic episodes. For example, directional volatility spillovers from the GBP markets to others reached a peak during the ERM crisis in 1992-93 (with the pound being suspended on September 16th, 1992).

[insert Figures 5 and 6 around here]

Finally, Figure 7 presents the net volatility spillovers from/to each of the four markets, which is obtained by estimating Eq. (12) using again 200-days rolling windows. Figure 7 suggests that the GBP and the JPY are, on average, receivers of volatility (apart from a few periods, such as the ERM 1992-93 crisis for the GBP markets), while the DM (EUR) and the CHF were mostly at the giving ends of the net volatility transmissions with almost equal magnitudes.

[insert Figures 7 around here]

3.4. Hedge ratios and portfolio weights

In this section, the implications of the preceding results for international portfolio diversification and currency risk management are examined.

The conditional variance estimates can be used to construct hedge ratios (Kroner and Sultan, 1993) and optimal portfolio weights (Kroner and Ng, 1998). Specifically, a long position in one exchange rate (say exchange i) can be hedged with a short position in a second exchange rate (say exchange j). Then, the hedge ratio between exchange rate i and j is

$$\beta_{ij,t} = h_{ij,t}/h_{jj,t}, \tag{14}$$

where $h_{ij,t}$ is the conditional covariance of i and j exchange rates, and $h_{jj,t}$ the conditional variance of j exchange rate at time t. The optimal portfolio weights between exchange rate i and j are calculated as

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}, \tag{15}$$

with

$$w_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases} \tag{16}$$

where $w_{ij,t}$ is the weight of the first exchange rate in a one dollar portfolio of two exchange rates i and j at time t. The weight of the second exchange rate is $1 - w_{ij,t}$.

The summary statistics for hedge ratios and portfolio weights computed from the conditional variance parameter estimates of the above DCC model are reported in Table 5.

[insert Table 5 around here]

According to panel a in Table 5, the average value of the hedge ratio between JPY and GBP is 0.54, while 1.04 between the CHF and the EUR in the pre-euro period. The corresponding values in the post-euro period are 0.29 and 0.97, respectively. These results are important in establishing that a 1$ long position in JPY can be hedged for 0.54 cents with a short position in the GBP market in the post-euro period, whilst for 0.29 cents in the post-euro period. As expected, from the preceding dynamic conditional correlation analysis, it is not, however, useful to hedge EUR with a short position in CHF, as these two exchange rates are very highly and positively correlated in both periods. The cheapest hedge is long GBP and short JPY, while the most expensive hedge is long CHF and short EUR in both periods. Another interesting finding is that, on average, all hedge ratios have declined in the post-euro period indicating that offsetting potential losses, on average, is cheaper in that period than in the pre-euro period, and which is in line with the preceding DCC model findings. Notice, in addition, that all hedge ratios in the pre-euro period record maximum values in excess of unity while in the post-euro period maximum values in excess of unity are recorded only between European currencies.

Panel b in Table 5 reports summary statistics for portfolio weights. For instance, the average weight for the EUR/GBP portfolio is 0.37 in the pre-euro period, indicating that for 1$ portfolio, 0.37 cents should be invested in EUR and 0.63 in GBP, whereas the average weight for the EUR/CHF portfolio indicates that 0.89 cents should be invested in EUR and 0.11 in the CHF. On average, EUR and JPY weights are lower while GBP weights are higher in the post-euro period compared to the pre-euro period.

4. Conclusion

This paper examines return co-movements and volatility spillovers of four major internationally traded currencies, namely the euro, the British pound, the Japanese yen and the Swiss franc against the US dollar, for the period before and after the introduction of the euro.

Employing various econometric techniques, several interesting results emerge. First, the results suggest evidence of significant co-movements and volatility spillovers across the four exchange returns series, but their magnitude is, on average, lower in the post-euro period compared to the pre-euro period. Over time, however, dynamic correlations and volatility spillovers show large variability and are positively associated with extreme economic episodes, such as stock market crashes, currency and debt crises and US recessions. Second, asymmetric influences of changes in the USD to dynamic correlations are observed in the post-euro period, as appreciations of the USD increase return co-movements.

Moreover, according to variance decomposition results from a generalized VAR and the corresponding generalized spillover index of Diebold and Yilmaz (2012), which overcomes pitfalls generally found in identification schemes of variance decompositions, the results of the existing literature are reappraised and refined. Specifically, the euro (Deutsche mark) is the dominant currency in volatility transmission with a net volatility spillover of 8% (15%) to all other markets, while the British pound is the dominant currency in receiving volatility from all other markets with a net volatility spillover of -11% (-13%) in the post- (pre-) euro period. Nevertheless, the nature of cross-market volatility spillovers is found to be bidirectional rather than unidirectional, with the highest volatility spillovers generally occurring between the European markets, and with increased influence of (to) the yen volatility to (from) the european markets' volatility since the launch of the euro.

The importance of these results and their implications for central bank intervention policies, international trade, risk management and portfolio diversification are then discussed. For instance, hedge ratio results suggest that, on average, is cheaper to offset potential losses in post-euro period than in the pre-euro period.

Overall, the results reveal significant differences in the extend and nature of return co-movements and volatility spillovers among major foreign exchange rates in the pre- and post- euro period.

Whilst, fundamentals are not taken explicitly into account in this study, an investigation of interdependencies between financial and real economic uncertainty, especially during periods of financial and economic crises, appears to be an interesting avenue for future research.

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Figure 1: Exchange rates

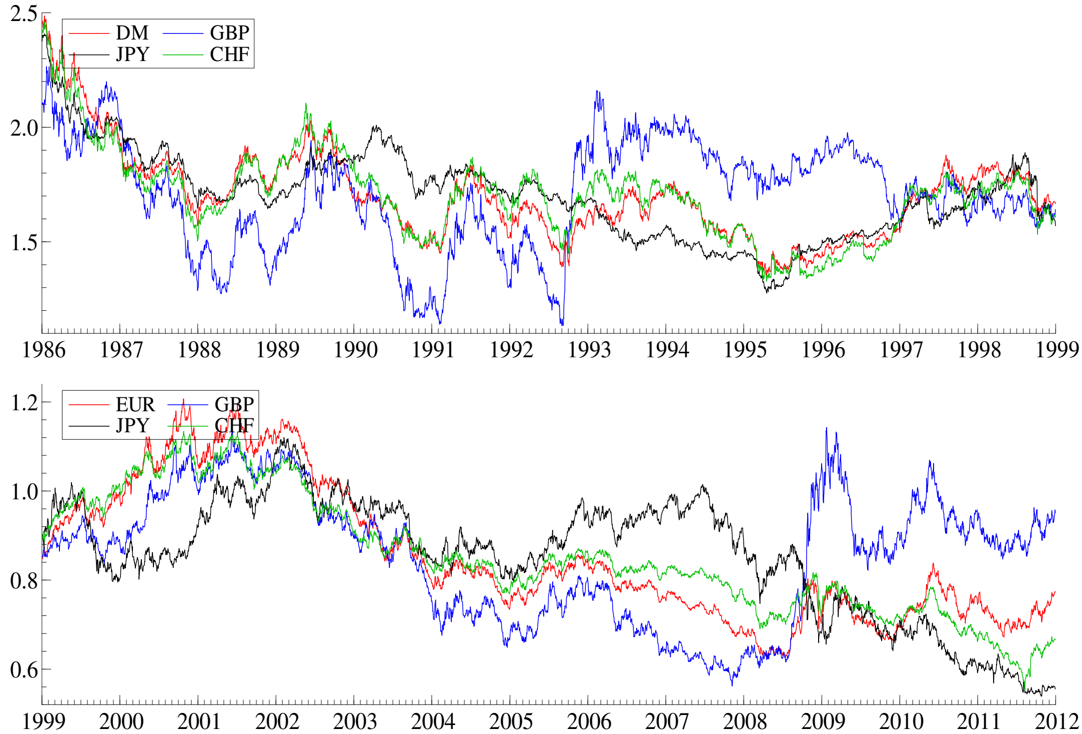

Figure 2: Exchange returns

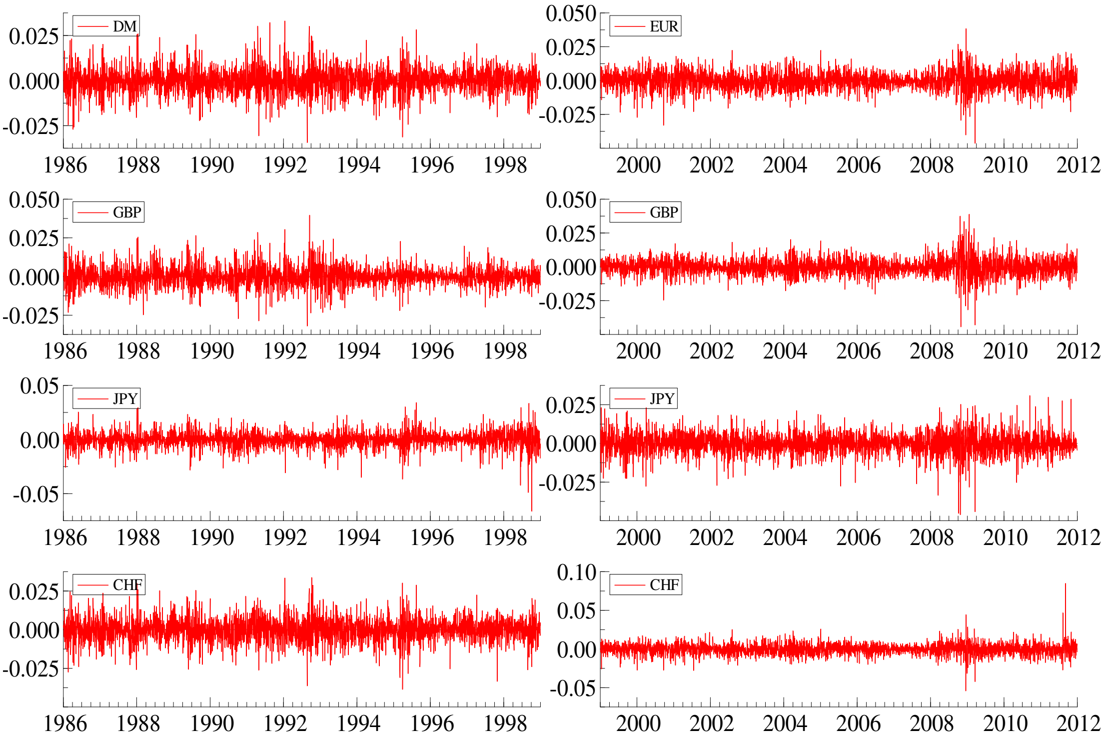

Figure 3: Dynamic conditional correlations

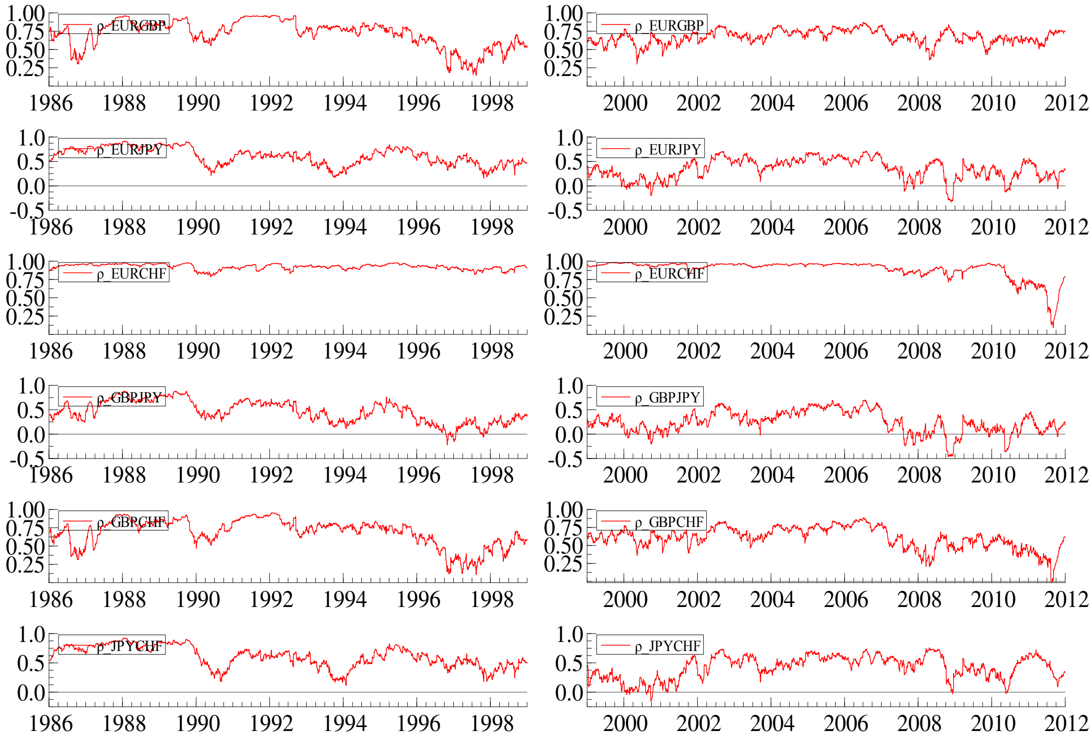

Figure 4: Total volatility spillovers, 200-days rolling windows

Figure 5: Directional volatility spillovers *FROM* four markets, 200-days rolling windows

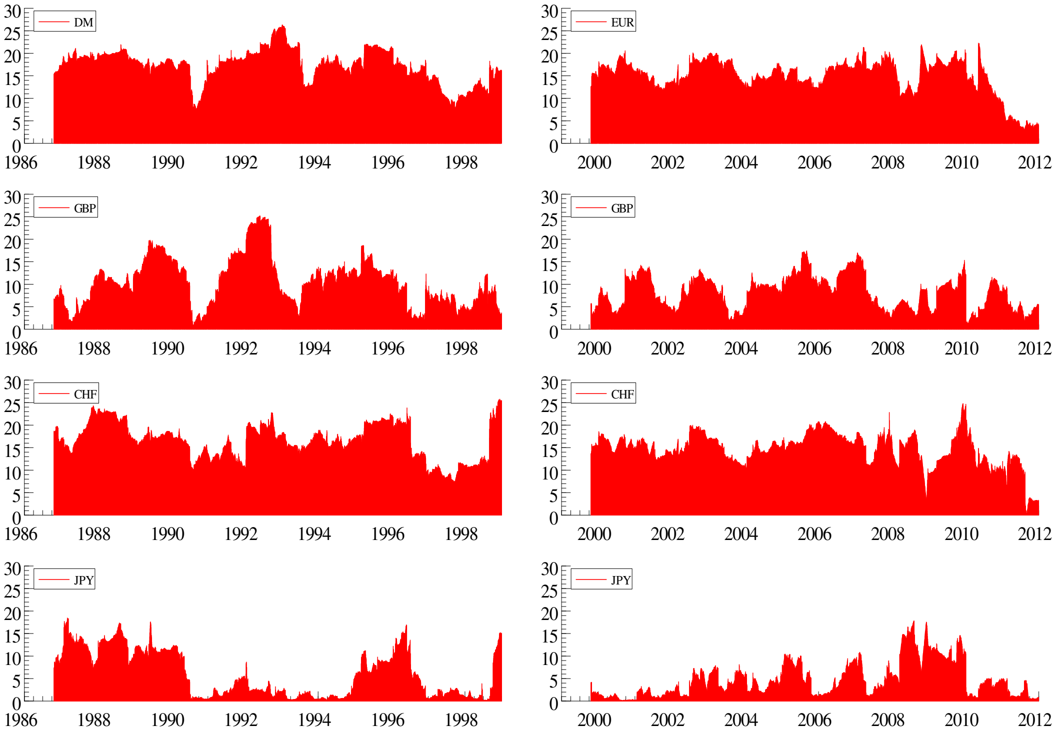

Figure 6: Directional volatility spillovers, TO four markets, 200-days rolling windows

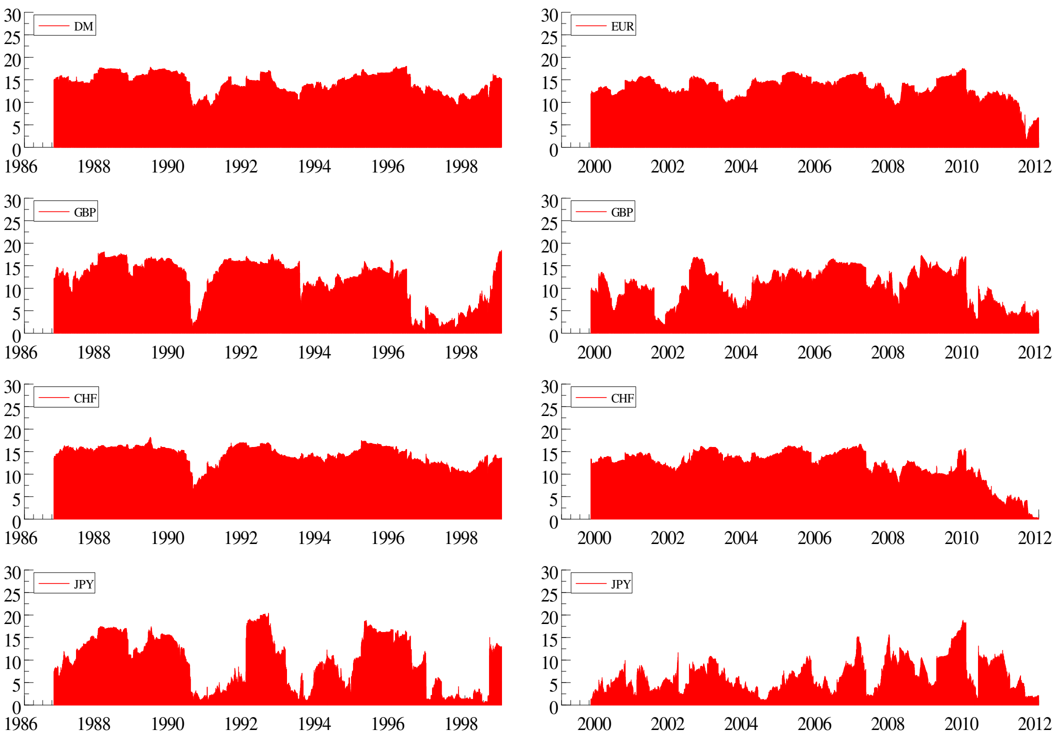

Figure 7: Net volatility spillovers, 200-days rolling windows

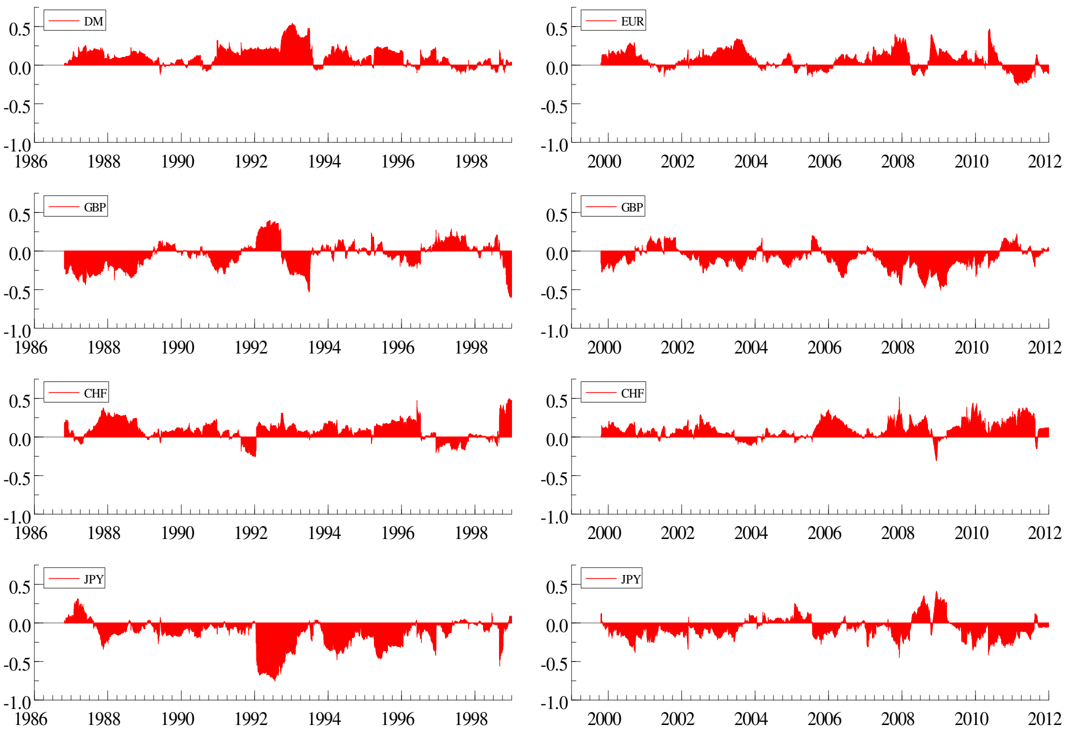

Table 1: Descriptive statistics of exchange returns

	Pre-Euro period (06.01.1896-31.12.1998)				Post-Euro period (04.01.1999-30.12.2011)			
	DM	GBP	JPY	CHF	EUR	GBP	JPY	CHF
Mean	-0.0001	-4.40e-05	-0.0002	-0.0001	-2.97e-05	2.24e-05	-0.0001	-0.0001
St. Dev.	0.0067	0.0063	0.0072	0.0075	0.0066	0.0061	0.0068	0.0072
Skewness	0.057	0.253	-0.556	-0.082	-0.166	0.034	-0.322	0.333
	[0.18]	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.81]	[0.00]**	[0.00]**
Excess	1.997	2.527	5.142	1.633	2.383	4.004	3.207	8.478
Kurtosis	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**
ADF	-55.42**	-52.93**	-54.91**	-55.13**	-56.25**	-55.44**	-58.89**	-57.84**
JB	548.02	909.73	3788.9	368.77	791.79	2194.1	1463.5	9896
	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**
Q(10)	19.35	38.66	16.71	18.32	8.348	23.58	13.90	6.836
	[0.04]*	[0.00]**	[0.08]	[0.05]*	[0.59]	[0.01]*	[0.18]	[0.74]
Q2(10)	249.16	316.86	341.22	195.67	329.65	992.25	141.18	104.78
	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**
ARCH(5)	20.14	28.69	33.53	18.21	29.18	74.58	18.35	13.48
	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**	[0.00]**
	Unconditional correlations							
	DM	GBP	JPY	CHF	EUR	GBP	JPY	CHF
EUR(DM)	1				1			
GBP	0.735	1			0.672	1		
JPY	0.593	0.458	1		0.259	0.127	1	
CHF	0.933	0.704	0.600	1	0.835	0.544	0.378	1

Notes: [] denote p-values. JB is the Jarque-Bera test for Normality, Q(10) and Q2(10) is the Ljung-Box statistic for serial correlation in raw series and squared series, respectively. ADF 5% and 1% critical values are -2.88 and -3.47, respectively. * 5% significant; ** 1% significant.

Table 2: Estimation Results of DCC model

	Pre-Euro Period (06.01.86-31.12.98)				Post-Euro Period (04.01.99-30.12.11)			
Panel a: 1-step, univariate GARCH estimates and univariate diagnostic tests								
	DM	GBP	JPY	CHF	EUR	GBP	JPY	CHF
Constant (m)	-0.0001	-0.0001	-0.0001	-0.0001	-0.0002	-0.0001	-0.00004	-0.0002
	(-0.1361)	(-1.334)	(-0.8004)	(-0.5792)	(-1.517)	(-0.9338)	(-0.3414)	(-1.423)
α	0.0564	0.0416	0.0772	0.0548	0.0300	0.0399	0.0357	0.0368
	(5.373)**	(5.092)**	(3.549)**	(4.732)**	(6.863)**	(6.152)**	(2.644)**	(3.959)**
β	0.9188	0.9511	0.8897	0.9072	0.9674	0.9525	0.9476	0.9566
	(55.59)**	(94.22)**	(26.27)**	(42.75)**	(196.0)**	(119.6)**	(43.33)**	(107.9)**
$Q(30)$	41.2779	27.7478	43.4689	39.4752	61.7173	31.0099	29.4321	38.8169
	[0.0674]	[0.5838]	[0.0532]	[0.1154]	[0.0005]**	[0.4149]	[0.4950]	[0.1299]
$Q^2(30)$	56.7194	20.8390	27.9273	36.5509	37.4172	27.8266	19.3338	74.5033
	[0.0023]**	[0.8929]	[0.5743]	[0.1906]	[0.1653]	[0.5796]	[0.9327]	[0.0000]**
Panel b: 2-step, correlation estimates and multivariate diagnostic tests								
ρ_{GBPEUR}	0.7613 (9.514)**				0.6236 (16.74)**			
ρ_{JPYEUR}	0.5131 (5.749)**				0.4122 (7.351)**			
ρ_{CHFEUR}	0.9478 (136.9)**				0.8720 (30.82)**			
ρ_{JPYGBP}	0.3907 (3.263)**				0.3152 (5.190)**			
ρ_{CHFGBP}	0.6929 (8.240)**				0.6336 (16.95)**			
ρ_{CHFJPY}	0.5422 (6.833)**				0.4436 (8.093)**			
α	0.0282 (11.92)**				0.0286 (10.22)**			
β	0.9694 (335.5)**				0.9637 (236.8)**			
df	6.5758 (20.71)**				7.6739 (18.80)**			
Log-Lik	53950.5				53047.4			
$H(30)$	510.632 [0.1388]				518.241 [0.1121]			
$H^2(30)$	512.652 [0.1302]				517.985 [0.1103]			
$Li-McL(30)$	510.525 [0.1395]				519.454 [0.1094]			
$Li-McL^2(30)$	511.754 [0.1362]				518.674 [0.1110]			

Notes: $Q()$ and $Q^2()$ are the Ljung-Box portmanteau tests statistic for serial correlation in the univariate standardized and squared standardized residuals, respectively. $H()$, $H^2()$ and $Li-McL()$, $Li-McL^2()$ are the multivariate versions of Ljung-Box statistic of Hosking (1980) and Li and McLeod (1981), respectively. () and [] t-values and p-values, respectively. * 5% significant; ** 1% significant.

Table 3: Dynamic correlations, recessions and depreciations/appreciation against the USD

Panel a: Pre-Euro Period (06.01.86-31.12.98)				
	(I)	(II)	(III)	(IV)
$Dep_{ij,t}$	0.0005	0.0005	0.0004	0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$App_{ij,t}$	0.0003	0.0003	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
$Rec_{ij,t}$		0.0017***	0.0019***	0.0021***
		(0.0005)	(0.0006)	(0.0007)
$Dep_{ij,t} \times Rec_{ij,t}$			0.0018*	
			(0.0011)	
$App_{ij,t} \times Rec_{ij,t}$				-0.0011
				(0.0011)
Trend	-6.8e-08	-2.5e-08	-2.6e-08	-2.3e-08
	(1.3e-07)	(1.3e-07)	(1.3e-07)	(1.3e-07)
Panel b: Post-Euro Period (04.01.99-30.12.11)				
	(I)	(II)	(III)	(IV)
$Dep_{ij,t}$	0.0009**	0.0009**	0.0010**	0.0009**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$App_{ij,t}$	-0.0001	-0.0001	-0.00004	-0.0002
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
$Rec_{ij,t}$		0.0010**	0.0012**	0.0011**
		(0.0004)	(0.0005)	(0.0005)
$Dep_{ij,t} \times Rec_{ij,t}$			-0.0005	
			(0.0009)	
$App_{ij,t} \times Rec_{ij,t}$				0.0009
				(0.0009)
Trend	1.8e-08	-2.7e-08	-2.7e-08	-2.4e-08
	(1.7e-07)	(1.7e-07)	(1.7e-07)	(1.7e-07)

Notes: All specifications include cross-section specific effects. Robust Standard Errors in parentheses. * 10% significant; ** 5% significant; *** 1% significant.

Table 4: Volatility spillovers

Panel a: Pre-Euro (06.01.86-31.12.98)					
	From (j)				
To (i)	DM CV	GBP CV	CHF CV	JPN CV	Contribution from others
DM CV	44.1	18.0	33.1	4.8	56
UK CV	27.5	51.9	18.6	1.9	48
CHF CV	34.3	13.7	44.8	7.2	55
JPN CV	8.9	3.7	12.3	75.1	25
Contribution to others	71	35	64	14	184
Contribution including own	115	87	109	89	Total Spillover
Net spillovers	15	-13	9	-11	Index= 46.0%

Panel b: Post-Euro (04.01.99-30.12.11)					
	From (j)				
To (i)	EUR CV	GBP CV	CHF CV	JPN CV	Contribution from others
EUR CV	60.1	13.7	18.4	7.7	40
UK CV	19.6	61.0	3.5	15.9	39
CHF CV	17.8	2.1	78.1	2.0	22
JPN CV	10.2	12.3	2.0	75.5	24
Contribution to others	48	28	24	26	125
Contribution including own	108	89	102	101	Total Spillover
Net spillovers	8	-11	2	2	Index= 31.3%

Notes: Values reported are variance decompositions for estimated VAR models for the conditional volatility (CV) obtained from the DCC model in Table 2. Variance decompositions are based on 10-step-ahead forecasts. In both periods, a VAR lag length of order 4 was selected by the Schwarz information criterion.

Table 5: Hedge ratios and portfolio weights summary statistics

	Pre-Euro (06.01.86-31.12.98)				*Post-Euro (04.01.99-30.12.11)*			
Panel a: Hedge ratios (long/short)								
	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max
EUR/GBP	0.79	0.23	0.15	1.43	0.77	0.14	0.31	1.21
EUR/JPY	0.61	0.24	0.14	1.44	0.33	0.21	-0.33	0.75
EUR/CHF	0.83	0.08	0.62	1.36	0.82	0.14	0.05	1.08
GBP/EUR	0.67	0.23	0.13	1.24	0.60	0.14	0.21	1.18
GBP/JPY	0.44	0.28	-0.18	1.26	0.21	0.21	-0.62	0.72
GBP/CHF	0.58	0.22	0.08	1.10	0.50	0.15	-0.01	0.92
JPY/EUR	0.64	0.22	0.15	1.63	0.37	0.23	-0.42	0.92
JPY/GBP	0.54	0.27	-0.30	1.74	0.29	0.27	-0.51	0.95
JPY/CHF	0.57	0.19	0.11	1.38	0.41	0.20	-0.10	0.93
CHF/EUR	1.04	0.09	0.56	1.27	0.97	0.16	0.15	1.23
CHF/GBP	0.85	0.25	0.12	1.63	0.75	0.22	-0.04	1.31
CHF/JPY	0.67	0.25	0.13	1.27	0.45	0.22	-0.22	0.89
Panel b: Portfolio weights (currency i/currency j)								
	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max
EUR/GBP	0.37	0.30	0.00	1.00	0.35	0.22	0.00	1.00
EUR/JPY	0.54	0.27	0.00	1.00	0.53	0.14	0.18	0.90
EUR/CHF	0.89	0.23	0.00	1.00	0.78	0.33	0.00	1.00
GBP/JPY	0.59	0.25	0.00	1.00	0.61	0.13	0.25	0.96
GBP/CHF	0.76	0.25	0.00	1.00	0.75	0.19	0.03	1.00
JPY/CHF	0.61	0.26	0.00	1.00	0.54	0.15	0.09	0.98