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

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This paper examines return co-movements and volatility spillovers between major exchange rates before and after the introduction of euro. Dynamic correlations and VAR-based spillover index results suggest significant return co-movements and volatility spillovers, however, their extend is, on average, lower in the post-euro period. Co-movements and spillovers are positively associated with extreme episodes and US dollar appreciations. The euro (Deutsche mark) is the dominant net transmitter of volatility, while the British pound the dominant net receiver of volatility in both periods. Nevertheless, cross-market volatility spillovers are bidirectional, and the highest spillovers occur between European markets.

Keywords: Exchange returns co-movement, Volatility spillover, VAR, Variance decomposition, Multivariate GARCH

JEL codes: C32; F31; G15

1. Introduction

The introduction of the euro more than a decade ago, on January 1, 1999, when the exchange rates of the participating countries were irrevocably pegged 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 1, 2002 and since then it has subsequently become the second most traded currency behind the US dollar in international usage according to the Bank for International Settlements (BIS). Specifically, 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

¹The 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%.
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. In addition, due to 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, 2005).

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

The literature on co-movements and volatility spillovers among exchange rate series since the introduction of the euro is ample. Inagaki (2007) uses residual cross-correlation functions (CCF) to investigates volatility spillovers between the British pound and the euro vis-à-vis the US dollar spot exchange rates between 1999 and 2004. The author finds a unidirectional volatility spillover from the euro to the pound. Nikkinen et al. (2006) offer 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 and 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) find that the dollar dominates the Japanese yen and the British pound vis-à-vis the euro between 2002 and 2006 in terms of both return and volatility spillovers.

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

Empirical studies have also examined exchange rate return co-movements and volatility spillovers

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2Own-market shocks and cross-market shocks are known as the ‘heat wave’ and ‘meteor shower’ effects, respectively, named by Engle et al. (1990) who pioneered research on volatility transmission.
in the period before the introduction of the euro. For instance, Kearney and Patton (2000) use data between 1979 and 1997 to examine exchange rate volatility transmission across important European Monetary System (EMS) currencies, namely, the French franc, Deutsche mark, Italian lira and the European Currency Unit. The authors find evidence of volatility transmission and that the mark plays a dominant position in terms of volatility transmission. Black and McMillan (2004) using exchange rate data for the Canadian dollar, Deutsche mark, French franc, Italian lira, British pound and the Japanese yen relative to the US dollar for the period 1974-1998 find significant volatility spillovers and return co-movements, especially among the European exchange rate series. Significant volatility spillovers between the Deutsche mark and Japanese yen against the US dollar over the period 1993-1995 are also evident in the study of Melvin and Melvin (2003).

Despite the fact that considerable amount of studies examined return co-movements and volatility spillovers either before or after the introduction of the euro, few studies formally compare both periods jointly. One of these exceptions is the study of Boero et al. (2011) who investigate the bi-variate 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 stable over time.

The aim of this study is to provide additional insights on the comparison of the extent and the nature of interdependencies and volatility spillovers of major exchange returns between the pre- and the post- euro period, which is the main 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). The generalized version of the spillover index overcomes common pitfalls found in the identification scheme of variance decompositions, as in the originally introduced spillover index of Diebold and Yilmaz (2009) and which was employed by McMillan and Speight (2010) in a similar context.

The results of the generalized version of the spillover index along with those from multivariate GARCH methodology, vector autoregressions (VAR) and generalized variance decompositions can be summarized as follows: (i) 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. (ii) 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 US dollar appreciations. (iii) The euro (Deutsche mark) is the dominant currency in net 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. (iv) The nature of cross-market volatility spillovers is found to be bidirectional, and the highest volatility spillovers occur 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. 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.

Following previous work on spot exchange rates data, where the spot rates are generally non-stationary, we 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 we employ the Dynamic Conditional Correlation (DCC) model proposed by Engle (2002).

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:

\[ r_t = \mu_t(\theta) + \epsilon_t, \quad \epsilon_t \mid \Omega_{t-1} \sim N(0, H_t) \]  
\[ \epsilon_t = H_t^{1/2} u_t, \quad u_t \sim N(0, I) \]  
\[ H_t = D_t R_t D_t \]

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, \( D_t = diag(h_{iit}^{1/2}, ..., h_{NIt}^{1/2})' \) 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:

\[ R_t = \text{diag}(q_{i_1,1}^{-1/2}, ..., q_{i_N,N}^{-1/2})Q_t\text{diag}(q_{i_1,1}^{-1/2}, ..., q_{i_N,N}^{-1/2}) \]  or \[ \rho_{ij,t} = \rho_{ji,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}q_{jj,t}}} \] (4)

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

\[ Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha u_{t-1}u_{t-1}' + \beta Q_{t-1} \] (5)

where \( u_t = (u_{1t}, u_{2t}, ..., u_{Nt})' \) is the \( N \times 1 \) vector of standardized residuals, \( \bar{Q} \) is the \( N \times N \) unconditional variance matrix of \( u_t \), and \( \alpha \) and \( \beta \) 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, we apply generalized vector autoregressive (VAR) methodology, 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 \( i = 1, 2, ..., N \), is due to shocks to the other, \( y_{jt} \), variables, for \( j = 1, 2, ..., N \), 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

\[ y_t = \sum_{i=1}^{p} \Theta_i y_{t-i} + \varepsilon_t \] (6)

where \( y_t = (y_{1t}, y_{2t}, y_{3t}, y_{4t}) \) is a vector of four endogenous variables, \( \Theta \) is a \( 4 \times 4 \) parameter matrix and \( \varepsilon_t \sim (0, \Sigma) \) is vector of independently and identically distributed disturbances. Then, the moving average representation is \( y_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i} \), where the \( 4 \times 4 \) 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 \( 4 \times 4 \) 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

$$
\phi^g_{ij}(H) = \sigma^{-1}_{ii} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2 \sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_1),
$$

(7)

where $\Sigma$ is the variance matrix of the error vector $\varepsilon$, $\sigma_{ii}$ the standard deviation of the error term for the $i$th equation and $e_i$ the selection vector with the one as the $i$th 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

$$
\tilde{\phi}^g_{ij}(H) = \frac{\phi^g_{ij}(H)}{\sum_{j=1}^{N} \phi^g_{ij}(H)}
$$

(8)

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

$$
S^g(H) = \frac{\sum_{i,j=1}^{N} \tilde{\phi}^g_{ij}(H) * 100}{\sum_{i,j=1}^{N} \phi^g_{ij}(H) * 100}.
$$

(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

$$
S^g_{i\rightarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}^g_{ij}(H)}{\sum_{j=1}^{N} \phi^g_{ij}(H)} * 100.
$$

(10)

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

$$
S^g_{i\rightarrow j}(H) = \frac{\sum_{j=1,j\neq i}^{N} \tilde{\phi}^g_{ji}(H)}{\sum_{j=1}^{N} \phi^g_{ji}(H)} * 100.
$$

(11)

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

$$
S^g_i = S^g_{i\rightarrow j}(H) - S^g_{i\leftarrow j}(H),
$$

(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.
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.\footnote{For the Swiss franc the null hypothesis of no ARCH effects is rejected at 10% level of significance.}

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.

Fig. 1 plots the evolution of the exchange rates over time.\footnote{Exchange rates are scaled by their means in Fig. 1.} 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.

Moreover, in Table 1, we 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 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, we 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.8

[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 geograph-
ically 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 re-
turns in both periods while the lowest between the yen-pound, yen-eur and the yen-franc.9 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, $\alpha$ and $\beta$, 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).10

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.11

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).12 The null hypothesis that

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8The 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.

9This 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.

10In 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.

11Restricting the sample size to match that in Boero et al. (2011), we also find that dynamic correlations of the
EUR and the GBP increased since the introduction of the euro from 0.59 during January 1994 - December 1998, to
0.61 during January 1999 - February 2002, and finally to 0.73 during March 2002 - November 2007.

12The $Z$-test statistic for the null hypothesis of no decrease in correlations is defined as: $T = \frac{Z_1 - Z_0}{\sqrt{\frac{1}{\sigma_0^2} + \frac{1}{\sigma_1^2}}}$, where
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. Fig. 2 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.

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. Fig. 2 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.

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? To answer that, we estimate panel regressions of the form

\[
\Delta \rho_{ij,t} = \mu_{ij} + \beta_1 Trend + \beta_2 Dep_{ij,t} + \beta_3 App_{ij,t} + \beta_4 Rec_{ij,t}
\]

\[
Z_0 = \frac{1}{2} \ln \left( \frac{1 + \hat{\rho}_0}{1 - \hat{\rho}_0} \right), \quad Z_1 = \frac{1}{2} \ln \left( \frac{1 + \hat{\rho}_1}{1 - \hat{\rho}_1} \right), \quad \hat{\rho}_0 \text{ and } \hat{\rho}_1 \text{ refer to pre-euro and post-euro correlations, respectively, } N_0 = 3286 \text{ and } N_1 = 3284.
\]

This test statistic is approximately normally distributed and is fairly robust to the non-normality of correlation coefficients.

\[13\] The graphs of the conditional variances and covariances are not presented but are available upon request.

\[14\] 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.
\[ + \beta_5 \text{Dep}_{ij,t} \times \text{Rec}_{ij,t} + \beta_6 \text{App}_{ij,t} \times \text{Rec}_{ij,t} + \epsilon_{ij,t} \]  

(13)

where $\Delta \rho_{ij,t}$ is the first difference of the estimated dynamic conditional correlation between return $i$ and $j$, $\mu_{ij}$ are country-specific effects and $\text{Trend}$ is a linear trend. To check for possible asymmetric influence of depreciations and/or appreciations of the US dollar on correlations we include two dummy variables: $\text{Dep}_{ij,t}$, which is equal to 1 if both currencies $i$ and $j$ depreciate jointly against the US dollar and 0 otherwise, and $\text{App}_{ij,t}$, 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, we include the dummy variable $\text{Rec}_{ij,t}$ defined as $\text{Rec}_{ij,t} = 1$ if the US economy was in recession and $\text{Rec}_{ij,t} = 0$ otherwise. Finally, we interact the US recession dummy variable with $\text{Dep}_{ij,t}$ and $\text{App}_{ij,t}$ to test whether 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 the $\text{Rec}_{ij,t}$ dummy variable 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, we 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).

The results of the degree and direction of volatility spillovers within and across the four exchange markets are shown in Table 4.
Before discussing the results, however, it is necessary to explain the rows and the columns of Table 4. The \(ij\)th 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.

Fig. 3 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.

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 \( S_{i<j}^{\tau}(H) \) in Eq. (10)) and the “Contribution from others” column (the sum of which is given by \( S_{j<i}^{\tau}(H) \) 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 Fig. 4. Specifically, panel A in Fig. 4 presents the directional volatility spillovers from each of the four markets to others (corresponding to the “Contribution to others” row in Table 4), while panel B in Fig. 4 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 this figure, 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 substantially 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).
Finally, Fig. 5 presents the net volatility spillovers from/to each of the four markets, which is obtained by estimating Eq. (12) using again 200-day rolling windows. Fig. 5 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 market), while the DM (EUR) and the CHF were mostly at the giving ends of the net volatility transmissions with almost equal magnitudes.

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 \textit{i}) can be hedged with a short position in a second exchange rate (say exchange \textit{j}). Then, the hedge ratio between exchange rate \textit{i} and \textit{j} is

\[ \beta_{ij,t} = \frac{h_{ij,t}}{h_{jj,t}}, \]

(14)

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

\[ w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}}, \]

(15)

with

\[ w_{ij,t} = \begin{cases} 0, & \text{if } w_{ij,t} < 0 \\ w_{ij,t}, & \text{if } 0 \leq w_{ij,t} \leq 1 \\ 1, & \text{if } w_{ij,t} > 1 \end{cases} \]

(16)

where \( w_{ij,t} \) is the weight of the first exchange rate in a one dollar portfolio of two exchange rates \textit{i} and \textit{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.

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

In this paper we examine 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, significant co-movements and volatility spillovers exist between 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 US dollar to dynamic correlations are observed in the post-euro period, as appreciations of the US dollar 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.

These results have important implications for central bank interventions, international trade, risk management and portfolio diversification. For instance, hedge ratio analysis suggests that, on average, is less costly to offset potential losses in the 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 inter-dependencies between financial and real economic uncertainty, especially during periods of financial and economic crises, appears to be an interesting avenue for future research.
Acknowledgment

I would like to thank the Editor (G. Geoffrey Booth) and the anonymous reviewers for insightful comments.

References


Figure 1: Exchange rates
Figure 2: Dynamic conditional correlations

- \( \rho_{\text{EURGBP}} \) over time from 1986 to 2012.
- \( \rho_{\text{EURJPY}} \) over time from 1986 to 2012.
- \( \rho_{\text{EURCHF}} \) over time from 1986 to 2012.
- \( \rho_{\text{GBPJPY}} \) over time from 1986 to 2012.
- \( \rho_{\text{GBPCHF}} \) over time from 1986 to 2012.
- \( \rho_{\text{JPYCHF}} \) over time from 1986 to 2012.
Figure 3: Total volatility spillovers, 200-day rolling windows
Figure 4: Directional volatility spillovers FROM and TO four markets, 200-day rolling windows

A) FROM four markets

B) TO four markets
Figure 5: Net volatility spillovers, 200-day rolling windows
Table 1: Descriptive statistics of exchange returns

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
</tr>
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<tbody>
<tr>
<td></td>
<td>DM</td>
<td>GBP</td>
</tr>
<tr>
<td>Mean</td>
<td>-0.0001</td>
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<tr>
<td>St. Dev.</td>
<td>0.0067</td>
<td>0.0063</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.057</td>
<td>0.253</td>
</tr>
<tr>
<td></td>
<td>[0.18]</td>
<td>[0.00]**</td>
</tr>
<tr>
<td>Excess</td>
<td>1.997</td>
<td>2.527</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>[0.00]**</td>
<td>[0.00]**</td>
</tr>
<tr>
<td></td>
<td>-55.42**</td>
<td>-52.93**</td>
</tr>
<tr>
<td>ADF</td>
<td>1998.02</td>
<td>909.73</td>
</tr>
<tr>
<td>JB</td>
<td>-55.42**</td>
<td>-52.93**</td>
</tr>
<tr>
<td>Q(10)</td>
<td>19.35</td>
<td>38.66</td>
</tr>
<tr>
<td>ARCH(5)</td>
<td>[0.00]**</td>
<td>[0.00]**</td>
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<td>Unconditional correlations</td>
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<td>GBP</td>
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<td>1</td>
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<tr>
<td>GBP</td>
<td>0.735</td>
<td>1</td>
</tr>
<tr>
<td>JPY</td>
<td>0.593</td>
<td>0.458</td>
</tr>
</tbody>
</table>
| CHF                  | 0.933       | 0.704        | 0.600        | 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

<table>
<thead>
<tr>
<th></th>
<th>Pre-Euro Period (06.01.96-31.12.98)</th>
<th>Post-Euro Period (04.01.99-30.12.11)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>DM</td>
<td>GBP</td>
</tr>
<tr>
<td>Constant (m)</td>
<td>-0.0001</td>
<td>-0.0001</td>
</tr>
<tr>
<td></td>
<td>(-0.1361)</td>
<td>(-1.334)</td>
</tr>
<tr>
<td>α</td>
<td>0.0564</td>
<td>0.0416</td>
</tr>
<tr>
<td>β</td>
<td>0.9188</td>
<td>0.9511</td>
</tr>
<tr>
<td></td>
<td>(55.59)**</td>
<td>(94.22)**</td>
</tr>
<tr>
<td>Q(30)</td>
<td>41.2779</td>
<td>27.7478</td>
</tr>
<tr>
<td></td>
<td>[0.0674]</td>
<td>[0.5838]</td>
</tr>
<tr>
<td>Q2(30)</td>
<td>56.7194</td>
<td>20.8390</td>
</tr>
<tr>
<td></td>
<td>[0.0023]**</td>
<td>[0.8929]</td>
</tr>
<tr>
<td>Panel B: 2-step, correlation estimates and multivariate diagnostic tests</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ρ</td>
<td>GBPEUR</td>
<td>0.7613 (9.514)**</td>
</tr>
<tr>
<td></td>
<td>JPYEUR</td>
<td>0.5131 (5.749)***</td>
</tr>
<tr>
<td></td>
<td>CHFEUR</td>
<td>0.9478 (136.9)***</td>
</tr>
<tr>
<td></td>
<td>GBPCHF</td>
<td>0.3907 (3.263)***</td>
</tr>
<tr>
<td></td>
<td>CHFJPY</td>
<td>0.6292 (8.240)***</td>
</tr>
<tr>
<td></td>
<td>CHFCHF</td>
<td>0.5422 (6.833)***</td>
</tr>
<tr>
<td></td>
<td>α</td>
<td>0.0282 (11.92)***</td>
</tr>
<tr>
<td></td>
<td>β</td>
<td>0.9694 (335.5)***</td>
</tr>
<tr>
<td></td>
<td>H</td>
<td>6.7578 (20.71)***</td>
</tr>
<tr>
<td></td>
<td>Log-Lik</td>
<td>53950.5</td>
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<tr>
<td></td>
<td>H(30)</td>
<td>510.632 (0.1388)</td>
</tr>
<tr>
<td></td>
<td>H2(30)</td>
<td>512.652 (0.1302)</td>
</tr>
<tr>
<td></td>
<td>Li</td>
<td>510.255 (0.1395)</td>
</tr>
<tr>
<td></td>
<td>Li – McL(30)</td>
<td>511.754 (0.1362)</td>
</tr>
</tbody>
</table>
| Notes: Q() and Q2() are the Ljung-Box portmanteau tests statistic for serial correlation in the univariate standardized and squared standardized residuals, respectively. H(), H2() and Li – McL(), Li – McL2() 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.
| Panel A: Pre-euro period (06.01.86-31.12.98) |
|---|---|---|---|
| (I) (II) (III) (IV) |
| \( \text{Dep}_{ij,t} \) & 0.0005 & 0.0005 & 0.0004 & 0.0005 & (0.0003) & (0.0003) & (0.0003) & (0.0003) |
| \( \text{App}_{ij,t} \) & 0.0003 & 0.0003 & 0.0003 & 0.0003 & (0.0003) & (0.0003) & (0.0003) & (0.0003) |
| \( \text{Rec}_{ij,t} \) & 0.0017*** & 0.0019*** & 0.0021*** & (0.0005) & (0.0006) & (0.0007) |
| \( \text{Dep}_{ij,t} \times \text{Rec}_{ij,t} \) & 0.0018* & (0.0011) |
| \( \text{App}_{ij,t} \times \text{Rec}_{ij,t} \) & 0.0001 & -0.0002 & -0.00004 & -0.0001 & (0.0004) & (0.0004) & (0.0004) & (0.0004) |
| 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) |
| \( \text{Dep}_{ij,t} \) & 0.0009** & 0.0009** & 0.0010** & 0.0009** & (0.0004) & (0.0004) & (0.0004) & (0.0004) |
| \( \text{App}_{ij,t} \) & -0.0001 & -0.0001 & -0.00004 & -0.0002 & (0.0004) & (0.0004) & (0.0004) & (0.0004) |
| \( \text{Rec}_{ij,t} \) & 0.0010** & 0.0012** & 0.0011** & (0.0004) & (0.0005) & (0.0005) |
| \( \text{Dep}_{ij,t} \times \text{Rec}_{ij,t} \) & 0.0005 & (0.0009) |
| \( \text{App}_{ij,t} \times \text{Rec}_{ij,t} \) & 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)

<table>
<thead>
<tr>
<th>To (i)</th>
<th>DM CV</th>
<th>GBP CV</th>
<th>CHF CV</th>
<th>JPN CV</th>
<th>Contribution from others</th>
</tr>
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<tbody>
<tr>
<td>DM CV</td>
<td>44.1</td>
<td>18.0</td>
<td>33.1</td>
<td>4.8</td>
<td>56</td>
</tr>
<tr>
<td>UK CV</td>
<td>27.5</td>
<td>51.9</td>
<td>18.6</td>
<td>1.9</td>
<td>48</td>
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<tr>
<td>CHF CV</td>
<td>34.3</td>
<td>13.7</td>
<td>44.8</td>
<td>7.2</td>
<td>55</td>
</tr>
<tr>
<td>JPN CV</td>
<td>8.9</td>
<td>3.7</td>
<td>12.3</td>
<td>75.1</td>
<td>25</td>
</tr>
<tr>
<td>Contribution to others</td>
<td>71</td>
<td>35</td>
<td>64</td>
<td>14</td>
<td>184</td>
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<tr>
<td>Contribution including own</td>
<td>115</td>
<td>87</td>
<td>109</td>
<td>89</td>
<td>Total Spillover</td>
</tr>
<tr>
<td>Net spillovers</td>
<td>15</td>
<td>-13</td>
<td>9</td>
<td>-11</td>
<td>Index= 46.0%</td>
</tr>
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Panel B: Post-euro (04.01.99-30.12.11)

<table>
<thead>
<tr>
<th>To (i)</th>
<th>EUR CV</th>
<th>GBP CV</th>
<th>CHF CV</th>
<th>JPN CV</th>
<th>Contribution from others</th>
</tr>
</thead>
<tbody>
<tr>
<td>EUR CV</td>
<td>60.1</td>
<td>13.7</td>
<td>18.4</td>
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<tr>
<td>UK CV</td>
<td>19.6</td>
<td>61.0</td>
<td>3.5</td>
<td>15.9</td>
<td>39</td>
</tr>
<tr>
<td>CHF CV</td>
<td>17.8</td>
<td>2.1</td>
<td>78.1</td>
<td>2.0</td>
<td>22</td>
</tr>
<tr>
<td>JPN CV</td>
<td>10.2</td>
<td>12.3</td>
<td>2.0</td>
<td>75.5</td>
<td>24</td>
</tr>
<tr>
<td>Contribution to others</td>
<td>48</td>
<td>28</td>
<td>24</td>
<td>26</td>
<td>125</td>
</tr>
<tr>
<td>Contribution including own</td>
<td>108</td>
<td>89</td>
<td>102</td>
<td>101</td>
<td>Total Spillover</td>
</tr>
<tr>
<td>Net spillovers</td>
<td>8</td>
<td>-11</td>
<td>2</td>
<td>2</td>
<td>Index= 31.3%</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Pre-euro (06.01.86-31.12.98)</th>
<th>Post-euro (04.01.99-30.12.11)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Hedge ratios (long/short)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Mean</td>
<td>St. dev.</td>
</tr>
<tr>
<td>EUR/GBP</td>
<td>0.79</td>
<td>0.23</td>
</tr>
<tr>
<td>EUR/JPY</td>
<td>0.61</td>
<td>0.24</td>
</tr>
<tr>
<td>EUR/CHF</td>
<td>0.83</td>
<td>0.08</td>
</tr>
<tr>
<td>GBP/EUR</td>
<td>0.67</td>
<td>0.23</td>
</tr>
<tr>
<td>GBP/JPY</td>
<td>0.44</td>
<td>0.28</td>
</tr>
<tr>
<td>GBP/CHF</td>
<td>0.58</td>
<td>0.22</td>
</tr>
<tr>
<td>JPY/EUR</td>
<td>0.64</td>
<td>0.22</td>
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<tr>
<td>JPY/GBP</td>
<td>0.54</td>
<td>0.27</td>
</tr>
<tr>
<td>JPY/CHF</td>
<td>0.57</td>
<td>0.19</td>
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<tr>
<td>CHF/EUR</td>
<td>1.04</td>
<td>0.09</td>
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<tr>
<td>CHF/GBP</td>
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</tr>
<tr>
<td>CHF/JPY</td>
<td>0.67</td>
<td>0.25</td>
</tr>
</tbody>
</table>

**Panel B: Portfolio weights (currency i/currency j)**

<table>
<thead>
<tr>
<th></th>
<th>Pre-euro (06.01.86-31.12.98)</th>
<th>Post-euro (04.01.99-30.12.11)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St. dev.</td>
</tr>
<tr>
<td>EUR/GBP</td>
<td>0.37</td>
<td>0.30</td>
</tr>
<tr>
<td>EUR/JPY</td>
<td>0.54</td>
<td>0.27</td>
</tr>
<tr>
<td>EUR/CHF</td>
<td>0.89</td>
<td>0.23</td>
</tr>
<tr>
<td>GBP/EUR</td>
<td>0.59</td>
<td>0.25</td>
</tr>
<tr>
<td>GBP/JPY</td>
<td>0.76</td>
<td>0.25</td>
</tr>
<tr>
<td>GBP/CHF</td>
<td>0.61</td>
<td>0.26</td>
</tr>
</tbody>
</table>