What causes exchange rate volatility? Evidence from selected EMU members and candidates for EMU membership countries

Nikolaos Giannellis*[a] and Athanasios P. Papadopoulos[b]
[a] Department of Economics, University of Ioannina, Ioannina, 45110, Greece
[b] Department of Economics, University of Crete, Rethymnon, 74100, Greece

Abstract

We allow for monetary, real, and financial variables to assess the relevant importance of each of the variables to exchange rate volatility in the case of selected EMU members and candidate countries. Ex-ante analysis shows that volatility in the Polish zloty/euro and the Hungarian forint/euro forex markets can be influenced by the monetary side of the economy. On the other hand, ex-post analysis shows that forex markets in France, Italy and Spain had been influenced, during the pre-EMU era, by monetary and real shocks. However, the Irish pound exchange rate per ECU had been affected by only real shocks.

Keywords: Exchange Rate Volatility; Bivariate GARCH; Volatility Spillover.

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* Corresponding author: Department of Economics, University of Ioannina, Ioannina, 45510, Greece. Tel: +302651005028, Fax: +302251028160. Email: ngianel@cc.uoi.gr

1. Introduction

In theoretical and empirical literature the impact of exchange rate volatility on the economy is a matter of a current debate. From one point of view, theoretical papers, such that of Obstfeld & Rogoff (1998), argue that exchange rate volatility is costly to the domestic economy. They illustrate that households and firms are negatively influenced through direct and indirect channels. The direct channel is based on the assumption that people are not happy with exchange rate fluctuations because they generate fluctuations in their consumption and leisure. The indirect channel assumes that firms set higher prices, in the form of a risk premium, in their attempt to hedge the risks of future exchange rate fluctuations. On the other hand, a different set of models, including that of Devereux & Engel (2003), supports the view that exchange rate volatility does not entail welfare costs. They show that domestic consumption is not affected if prices are fixed to the currency of the foreign country.

However, empirically it is more common that exchange rate volatility provokes costs for the domestic economy. In general, welfare costs are higher for developing countries than for developed countries. Egert & Morales-Zumaquero (2005) find that exchange rate volatility weakens exports in Central and Eastern European (CEE) countries with different effects across countries. An active application of the argument that exchange rate volatility is costly is the European Economic and Monetary Union (EMU). Exchange rate stability is crucial for the effectiveness of monetary convergence to the euro zone. In other words, in line with the theory of optimum currency area, the lower the exchange rate volatility, the greater the ability of two countries to share a common currency. Hence, the Maastricht Treaty has set the obligation of EMU candidate countries to retain exchange rate stability vis-à-vis the euro for at least two years before adopting the single currency.

The empirical literature on the direct examination of exchange rate volatility in EMU candidate countries is not rich. Bask & Luna (2005) found that with the creation of EMU, most of the European countries have been more stable and less volatile. However, specific facts can change the behavior of exchange rates. For instance, most of the currencies became more volatile when Denmark voted against the euro. Finally, they did not find evidence that monetary policy integration can negatively affect exchange rate stability.

A study that is more relevant – to EMU candidate countries – is that of Kocenda & Valachy (2006), which examines the behavior of exchange rate volatility for Poland, Hungary, Slovakia, and Czech Republic under fixed and floating exchange rate regimes. Applying a TGARCH model in order to capture any asymmetric effects in the process, they find that volatility is greater under a floating than under a fixed regime. This implies that the type of the regime is an important factor for exchange rate volatility.[1] However, exchange rate volatility patterns are different across countries. In addition, they find that the effect of the interest rate differential on volatility is small, but it becomes higher under floating regimes. This is because under a fixed regime monetary policy is not independent and domestic interest rates are set by the foreign "anchor" country.

Kobor & Szekely (2004) find that exchange rate volatility (vis-à-vis the euro) in four CEE countries is subject to regime switching. Cross-correlations between exchange rates are higher when both exchange rates are in the high volatility regime, which implies higher spillover effects when exchange rates are volatile. In general,

[1] Similarly, Rose (1996) argues that the exchange rate regime does matter in explaining exchange rate volatility. In an empirical application he finds that there is a positive and significant relationship between exchange rate band and exchange rate volatility. In contrast, Frenkel & Goldstein (1987) argue that exchange rate regimes may not be significant for volatility. They claim that macroeconomic fundamentals should play a significant role, since the real sources of exchange rate volatility are bad policies and market inefficiencies.

they find that high volatility is linked with depreciation periods, while low volatility comes with slow appreciation trends (for the domestic currency).

In the present study, consistent with the Maastricht exchange rate criterion, we examine the behavior of four CEE countries' currencies vis-à-vis the euro. To be specific, we aim to define the sources of volatility of those exchange rates. We allow for monetary variables, real variables, and financial variables to assess the relevant importance of each of the variables to (potential) exchange rate volatility. In addition, we conduct the same analysis for selected EMU and former European Monetary System (EMS) members in order to examine the dynamic relationship among the corresponding exchange rates vis-à-vis the ECU and the above variables of interest during the pre-EMU period. Namely, the empirical investigation involves an ex-ante analysis for the cluster of CEE countries and an ex-post analysis for the cluster of EMU countries.

This paper contributes by shedding light on a number of important policy issues. First, the ex-ante analysis provides important information to the monetary authorities about which part of the economy induces most exchange rate volatility. Thanks to this information, policy makers in CEE countries are aware of the channels which transmit volatility to the exchange rate and by applying the appropriate policy can stabilize those disturbances in order to avoid excessive fluctuation of their exchange rates per euro (for those countries which follow a free-floating or managed-floating regime) and excessive pressure on the currency (for those countries which have chosen to peg the exchange rate at the fixed central rate). Second, we can infer whether monetary-based or real-based shocks are most important in explaining exchange rate behavior. This information is helpful in evaluating the applied exchange rate policy against the euro until the time of adoption of the single currency. If monetary shocks are more important then a fixed regime is appropriate. In contrast, if real shocks drive exchange rate developments then a floating exchange rate regime seems to be appropriate. Third, our results indicate how a potential entry of the CEE countries in the EMU can affect the euro zone itself. We investigate whether exchange rate volatility across countries has a common source which can be treated by a common monetary policy (i.e. ECB's monetary policy). Finally, the ex-post analysis informs us whether the source of exchange rate volatility can be accused, inter alia, for the EMS crisis.

2. Theoretical Background

In this section we explain why we expect the existence of dynamic interdependence between the foreign exchange (forex) market and the other side of the economy, such as the monetary-side, the real-side and the stock market. Given that the exchange rate is an endogenous variable, exchange rate volatility depends on economic fundamentals' volatility. On the other hand, macroeconomic fundamentals may be volatile if their actual rates deviate from their long-run (sustainable) values. This is also the primary origin of exchange rate misalignment. Actually, exchange rate volatility corresponds to short-run fluctuations of the exchange rate around its long-run trends. Exchange rate misalignment refers to a significant deviation of the observed exchange rate from its equilibrium rate. Both notions are closely related to each other. This is because a highly misaligned exchange rate will be highly volatile at present and in the future in order to find its equilibrium rate (by its own forces or by government interventions in the forex market).

The above imply that the exchange rate will be at equilibrium levels if the macroeconomic fundamentals are at their sustainable levels. As a result, the exchange rate is not expected to exhibit high volatility in response to the macroeconomic condition. However, exchange rates may be volatile even if macroeconomic fundamentals do not deviate significantly from their sustainable values (i.e. the exchange rate is not misaligned). This is because other factors, such as financial markets, affect the behavior of exchange rates as well. Devereux & Lane (2003) find that standard optimal currency area variables (trade interdependence, economic shocks, country size, etc.) have the same effects on developed and developing countries in explaining bilateral exchange rate volatility. On the other hand, financial variables are more important for developing countries. Higher external financial linkages increase exchange rate volatility insignificantly in developed countries, while they decrease volatility in developing countries. Higher internal finance (i.e. higher financial depth) increases exchange rate volatility in developed countries and decreases it in developed countries.

Financial development, measured by financial depth and financial intermediaries' efficiency, may influence the behavior of exchange rates. Especially for developing countries, financial development has been an important factor in economic growth. King & Levine (1993) find that there is a significant positive relationship between financial depth and economic growth. Fink et al. (2004) find significant evidence that bond markets and banking sectors promote economic growth in developing countries. On the other hand, stock markets have the lowest positive impact on economic growth in the examined developing countries.[2] In addition, they argue that the effect of finance on growth varies across countries. This is due to the phase of the development cycle of the economy. In transition countries, the impact of finance on growth is very important at early stages of transition, while for the examined developed countries the financial sector affects the rate of economic growth insignificantly. The same

[2] This is due to the low level of stock market development in these countries. Minier (2003) shows that the finance–growth nexus is less strong in countries with low stock market capitalization.

conclusion arises from Fink et al. (2005), who show that this relationship is stronger in transition economies than in mature economies. So, financial development affects exchange rate behavior through the mechanisms of the finance–growth nexus (i.e. by affecting the performance of real economic activity).

3. Data and Preliminary Statistics

The data are taken from the *International Financial Statistics* of the International Monetary Fund and the *Eurostat Statistics Database* of the European Commission. The dataset includes monthly observations on nominal exchange rates vis-a-vis the euro/ECU, nominal interest rates, industrial production indices and national share prices indices for Poland and Hungary (from 1991:01 to 2007:12), Czech Republic and Slovak Republic (from 1993:1 to 2007:12), France, Italy Spain, Ireland (from 1980:01 to 1998:12) and the EU/Euro Area (from 1980:01 to 2007:12).[3] Specifically, the exchange rate return (e) stands for the first log difference of the nominal exchange rate per euro (ECU rates are used prior to 1999). Stock market development is captured by the national share prices index. In our dataset, stock returns (s) are calculated as the first log difference of stock prices in each domestic country. In addition, the output variable (y) stands for the first log difference of the Industrial Production (IP) differential, which is the difference between the EU/Euro Area's IP and the national IP index. Similarly, the monetary variable (r) is measured by the first difference of the interest rate differential, which is the difference between national and EU/Euro Area interest rates. Subject to data availability, money market rates have been preferred in order to capture any movements in the money market. Where money market rates are not available, the corresponding lending rates are applied. Moreover,

[3] Nominal exchange rate and national share prices index have not been retrieved for the EU/Euro Area.

German interest rates and the IP index are used before 1994 as proxies of the corresponding EU series.

The following tables and figures present a clear view of the behavior and the volatility of the variables used in our dataset. Figure 1 shows that the Polish zloty exchange rate per euro is unstable during the period, but the degree of instability is not high. In contrast, the interest rate differential is highly volatile from the beginning of the estimated period until 2002. Stock prices and the IP differential are significantly volatile with the former being more volatile during the period 1993–1995. Figure 2 illustrates that the forint exchange rate per euro exhibits relatively low volatility. Once again the interest rate differential and the IP differential are highly unstable, while the stock returns variable exhibits moderate volatility.

[Insert Figure 1 here]

[Insert Figure 2 here]

[Insert Figure 3 here]

[Insert Figure 4 here]

In the case of the Czech Republic, Figure 3 shows that the crown exchange rate vis-à-vis the euro displays low volatility except during some single periods (1997–1999 and 2002), in which it was relatively less stable. Despite the other two cases, those of Poland and Hungary, the interest rate differential seems to be in general stable. However, a significant outlier is observed in 1997. In addition, stock prices and the IP differential exhibit retained volatility. In Figure 4, the Slovak crown exchange rate vis-à-vis the euro includes two outliers (in 1993 and 1998) indicating some degree of exchange rate volatility. The IP differential has relatively low volatility for the whole period, while the Slovak stock market presents adequate stability only after

1995. The already high level of interest rate differential volatility expands during 1998 and 2000.

Turning to the cluster of EMU countries, Figure 5 shows that the French franc exchange rate vis-à-vis the ECU exhibits low volatility as a result of the participation of France into the European Monetary System (EMS) since 1979. On the contrary, the interest rate differential has been greatly volatile, especially during the period 1981-1982 and after the EMS crisis (1993). On the other hand, the remaining series exhibit relatively low volatility. Similarly, Figure 6 illustrates that the Italian lira exchange rate vis-à-vis the ECU has been low volatile apart from two small in duration periods, i.e. in 1985 and during the post-EMS period. The interest rate differential was significantly volatile but, less volatile compared to the France's case. However, volatility increases rapidly in 1993, i.e. at the time of the abandonment of the EMS. For the remaining variables, the Italian stock market seems to be low volatile, while the IP differential exhibits relatively high volatility.

[Insert Figure 5 here]

[Insert Figure 6 here]

The Spanish peseta exchange rate vis-à-vis the ECU along with the rest of the variables of interest is presented in Figure 7. The exchange rate has exhibited low volatility with an exception of signs of high volatility in 1983. Similarly, the already high volatility of the interest rate differential is expanded in 1982. Spanish stock market has exhibited relatively low volatility, while the IP differential has been significantly volatile. As in the cases of France and Italy, the Irish pound exchange rate vis-à-vis the ECU, shown in Figure 8, was remarkably stable apart from the period just after EMS crisis. The plot of the growth of interest rate differential implies that this series was low volatile. Though, a significant outlier in the relatively low volatility of the interest rate differential is as well observed in 1993. Although, the Irish stock prices index was in general stable, a negative shock in the Irish stock market in 1988 has increased the estimated volatility. Finally, the plot of the IP differential shows that the IP differential exhibits retained volatility.

[Insert Figure 7 here]

[Insert Figure 8 here]

Preliminary statistics (Tables 1 and 2) reveal that the normality hypothesis can be accepted for the output differential series (only in the cluster of CEE countries) and the Czech stock return variable. For the rest of the variables, non-normality is mainly due to excess kurtosis (i.e. kurtosis > 3). In that case, the distribution is leptokurtic indicating the presence of extreme values in the distribution of those variables. The ADF test confirms that all series, apart from the Slovak and Czech output differentials, are covariance stationary. These two variables have been found to be stationary by applying two alternative unit root tests. For both series the Phillips-Perron (PP) test rejects the unit root hypothesis and the KPSS test confirms that stationarity is accepted.[4] In line with the view that the above figures provide, standard deviation estimates confirm that the less stable series are those of the interest rate differentials. While the standard deviation is a measure of absolute dispersion, the ratio of the mean to the standard deviation (μ/σ) stands for a measure of relative dispersion of the series. A high value of this relative dispersion implies that the standard deviation is small in comparison with the magnitude of the mean. This implies that the higher the measure of relative dispersion (μ/σ), the lower the volatility

[4] The results from the PP and the KPSS tests are not presented here. However, they will be available on request.

of the series. In our dataset, this measure of relative dispersion shows that the most volatile variables are those of the interest rate differentials.[5]

[Insert Table 1 here]

[Insert Table 2 here]

4. VAR Analysis

As a preliminary analysis we attempt to define the causal relationships among the variables of interest. In other words, we need to know whether exchange rate movements are driven by the rest of the variables or whether the exchange rate instead causes movements in monetary, real, and financial variables. In addition, the relative importance of each innovation in an exogenous variable in explaining the variance of the endogenous variable is under investigation. To answer these questions we apply a pair-wise Granger causality test, and after estimating a multivariate VAR model we perform a variance decomposition analysis.

The Granger (1969) approach to the question of whether monetary, real, or financial variables cause exchange rate movements is to see how much of the current exchange rate return can be explained by past values of those variables. For example, the exchange rate is said to be Granger-caused by the interest rate differential if the latter helps in the prediction of the former, or equivalently if the coefficients on the lagged interest rate differential are statistically significant. Technically, we regress the following regressions

$$e_t = a_0 + a_1 e_{t-1} + \ldots\ldots + a_k e_{t-k} + b_1 r_{t-1} + \ldots\ldots + b_k r_{t-k} + u_t \qquad (1)$$

$$r_t = a_0 + a_1 r_{t-1} + \ldots\ldots + a_k r_{t-k} + b_1 e_{t-1} + \ldots\ldots + b_k e_{t-k} + u_t \qquad (2)$$

[5] The estimates of this measure of relative dispersion should be interpreted with caution. This is because the relative dispersion is going to be zero if the mean is zero.

The null hypothesis of no Granger causality is described by $b_1 = b_2 = ... = b_k = 0$ while Wald statistics (F statistics) are utilized. The following table illustrates the output of the Granger causality test.

[Insert Table 3 here]

Although the main interest is focused on causality dynamics between the exchange rate and the rest of the variables, Table 3 and Table 4 present the results of the pair-wise Granger causality test for all possible combinations of the variables. The results show that movements in interest rate differentials can Granger cause movements in the exchange rate for the cases of Poland and the Slovak Republic (Table 3) and for France, Spain and Ireland (Table 4). The causality effect in the opposite direction is active only for Hungary and Ireland. In contrast, stock returns cannot Granger cause exchange rate returns in any CEE country (Table 3). For the EMU countries (Table 4), this effect is observed only in the case of France. However, exchange rate movements can drive stock returns for the cases of the Czech Republic and Spain. Similarly, exchange rate changes cause movements in the IP growth differential for Poland and the Slovak Republic (Table 3) and for Italy (Table 4), while this effect does not hold in the opposite direction.

To continue the analysis, we consider possible causality effects among the rest of the variables. This task is undertaken to capture both direct and indirect causality effects. To give an example, the evidence reveals that stock market developments cannot cause movements in the exchange rate in any CEE country. However, stock returns can Granger cause movements in interest rate differentials (for the cases of Poland and Hungary), which in turn can Granger cause exchange rate returns. Despite the evidence of Granger causality between stock returns and the interest rate differential, indicating the indirect effect of the stock market on the exchange rate, there is a lack of pair-wise causality between the rest of the variables (y and r; y and s), except in the case of Slovakia in which stock returns can cause movements in the IP differential.

[Insert Table 4 here]

Furthermore, to capture the relative importance of each innovation in the variance of the endogenous variables, we perform a variance decomposition analysis. After estimating a VAR model (e, r, s, and y stand for the endogenous variables), the variance decomposition of the forecast error of a given variable illustrates the relative importance of all variables included in the VAR in explaining the variability of the given variable. Tables 5a–5d present the decompositions of 10-period forecast error variances for Poland, Hungary, the Czech Republic, and the Slovak Republic, respectively.[6]

[Insert Table 5a here]

[Insert Table 5b here]

This analysis shows that all variables' forecast error variance is mainly explained by their own innovations. For the case of Poland, the exchange rate return can explain 97.52% of its forecast error variance; the interest rate differential explains 91.24% of its forecast error variance, while stock return and the IP differential can explain 95.06% and 95.40% of their forecast error variances, respectively. Overall, the exchange rate seems to be the less endogenous variable in the VAR systems. In contrast, interest rate differentials and stock returns are the most endogenous variables. All variables are significantly affected by exchange rate fluctuations. To give an example, consider the case of the Czech Republic. Table 5c shows that

[6] These estimates should be examined with caution because they are very sensitive to the order of the variables in the VAR model. Namely, the results may change significantly if we change the order of the variables. For example, Table 3a shows that exchange rate return explains 97.52% of its variance by its own innovations. However, by setting the exchange rate return last in the sequence of the variables in the same VAR model, this percentage is reduced to 93.57%.

exchange rate fluctuations have 4.77% and 6.09% impacts on the interest rate differential and stock return forecast error variances, respectively. In line with the implications derived from the Granger causality test, interest rate differential innovation has a small but important role in affecting the exchange rate return. About 2.04% of the forecast error variance of the Slovak exchange rate is due to the interest rate differential. Similarly, stock market innovation explains a small percentage (1.10% in the case of Poland) of the exchange rate's variance.

[Insert Table 5c here]

[Insert Table 5d here]

Accordingly, Tables 5e – 5g present the decompositions of 10-period forecast error variances for France, Italy, Spain and Ireland, respectively. As in the cases of the CEE countries, all variables' forecast error variance is mainly explained by their own innovations. However, three important differences in comparison to the previous results should be mentioned. First, as opposed to the CEE countries, the exchange rate return series seems to be the most endogenous variable in France's and Ireland's VAR models. Second, the role of the interest rate differential innovation in affecting the exchange rate return is much more significant in the selected EMU countries than in CEE countries. Finally, although all variables are affected by exchange rate fluctuations the most significant impact on the remaining endogenous variables' variance is not driven by exchange rate innovations. In the case of France, the exchange rate fluctuation can explain 5.90% of the forecast error variance of the interest rate differential, while stock returns innovation can explain 6.48% of the forecast error variance of the same variable. Similarly, only 3.92% of the forecast error variance of the stock returns variable is due to exchange rate fluctuation. About

7.68% of stock returns' variance is explained by the interest rate differential fluctuation.

[Insert Table 5e here]

[Insert Table 5f here]

[Insert Table 5g here]

[Insert Table 5h here]

5. Multivariate GARCH Analysis

The dynamic interdependence among the variables of interest can also be investigated by examining volatility dynamics. In this study we aim to define the short-run dynamic relationships between the exchange rate and the rest of the variables. Furthermore, we investigate the existence of volatility spillovers in any direction. In other words, we attempt to examine whether volatility of one variable can be transmitted to another variable. Because of our concern with exchange rate volatility, we focus on the examination of the assumption that other variables (i.e. interest rate differential, IP differential, and stock return) export volatility to the foreign exchange market. In addition, the spillover effect in the opposite direction is also tested.

In a univariate framework, volatility changes are modeled by an ARCH model introduced by Engle (1982). The ARCH model is given by:

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \ldots + \alpha_p u_{t-p}^2 \quad (3)$$

which can be written as:

$$\sigma_t^2 = z_t' \cdot \vartheta \quad (4)$$

where $z_t = (1, u_{t-1}^2, u_{t-2}^2, ..., u_{t-p}^2)$ and $\vartheta = \left(\omega, \alpha_1, \alpha_2, ..., \alpha_p\right)'$. Bollerslev (1986) extended the ARCH model into the GARCH(p,q) model of the following form:

$$\sigma_t^2 = \omega + \sum_{i=1}^{p} \alpha_i u_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \tag{5}$$

where $\omega > 0, \alpha_i \geq 0, \beta_j \geq 0$. Expression (13) shows that the conditional variance is a function of a constant term, the ARCH term (which is news about volatility from the previous period) and the GARCH term (which is the last period's variance).

However, the univariate GARCH(p,q) model is not appropriate when volatility spillovers are considered. To overcome this limitation, Hamao et al. (1990), Theodosiou & Lee (1993), and Kim (2001), among others, have applied a two-stage approach. In the first stage, a GARCH model for all of the series is estimated to get standardized residuals and squared standardized residuals. In the second stage, the standardized and squared standardized residuals are substituted into the mean and volatility equations of the exchange rate GARCH model.

An alternative but more efficient and powerful procedure is to employ a multivariate GARCH (MGARCH) model, introduced by Bollerslev et al. (1988). An MGARCH model helps in defining the dynamic relationships between the exchange rate return and the rest of the variables. Moreover, it captures any possible reciprocal volatility spillover effects between any pairs of the variables. Actually, Bollerslev et al. (1988) introduced the half-vec (vech) MGARCH model. To illustrate this model, consider a K-dimensional vector of time series variables and a serially uncorrelated but conditionally heteroskedastic K-dimensional vector of error terms, $u_t = (u_{1,t}, u_{2,t}, ..., u_{K,t})'$, which have a conditional distribution with zero mean and conditional covariance matrix Σ_t. The vector u_t follows a multivariate GARCH (p,q) process if:

$$u_t \mid \Omega_{t-1} \sim N(0, \Sigma_t)$$
$$vech(\Sigma_t) = \gamma_0 + \sum_{i}^{p} \Gamma_i vech(u_{t-i} u'_{t-i}) + \sum_{j=1}^{q} B_j vech(\Sigma_{t-j}) \quad (6)$$

where Ω_{t-1}stands for the information set; vech(.) is the half-vectorization operator which holds the elements of the quadratic $(K \times K)$ matrix from the main diagonal downwards in a $\frac{1}{2}K(K+1)$-dimensional vector; γ_0 is a $\frac{1}{2}K(K+1)$-dimensional column vector including time invariant variance-covariance elements; and Γ_i and B_j are fixed $[\frac{1}{2}K(K+1) \times \frac{1}{2}K(K+1)]$ coefficient matrices.

The fact that the parameter space of the above MGARCH model has a large dimension and that the estimation procedure requires numerous iterative calculations explains the limited empirical application of the half-vec model. A number of alternative procedures have been proposed to reduce the parameter space in order to ensure computational feasibility and suitable properties of the conditional covariances. Bollerslev et al. (1988) introduced the diagonal MGARCH model in which Γ_i and B_j are diagonal matrices. Similarly, Bollerslev (1990) introduced the constant conditional correlation (CCC) MGARCH model which is characterized by time varying conditional variances and covariances but constant conditional correlation. Although the CCC-MGARCH model significantly reduces the parameter space in (6), a significant drawback of this model is that by reducing the parameter space cross-sectional dynamics are excluded by construction.

On the other hand, the BEKK model (Engle & Kroner, 1995) consists of a multivariate volatility specification model which allows for time-varying conditional correlation (TVCC) and cross-sectional dynamics.[7] The TVCC-MGARCH (p,q) model is of the following form:

$$\Sigma_t = A'A + \sum_{n=1}^{N}\sum_{i=1}^{p}\Gamma'_{ni}\, u_{t-i}u'_{t-i}\,\Gamma_{ni} + \sum_{n=1}^{N}\sum_{j=1}^{q}B'_{nj}\,\Sigma_{t-j}B_{nj} \tag{7}$$

In (7), Σ_t is a $K \times K$ conditional covariance matrix; A is a $K \times K$ upper triangular matrix; and Γ_{ni} and B_{ni} are $K \times K$ parameter matrices. A significant advantage of the BEKK model is that only squared terms are included in the right-hand side of (7), which guarantees the positive value of the variance. In addition, the BEKK model is said to be stationary if all eigenvalues of the matrix $\sum_{n=1}^{N}\sum_{i=1}^{p}\Gamma'_{ni}\otimes\Gamma'_{ni} + \sum_{n=1}^{N}\sum_{j=1}^{q}B'_{nj}\otimes B'_{nj}$ have a modulus of less than one (Engle & Kroner, 1995). Moreover, in its simplest specification form (N = p = q = 1), the BEKK MGARCH is reduced to a TVCC-MGARCH (1,1) model of the following form:

$$\Sigma_t = A'A + \Gamma'_{11}\, u_{t-1}u'_{t-1}\,\Gamma_{11} + B'_{11}\,\Sigma_{t-1}B_{11} \tag{8}$$

Engle & Kroner (1995) show that the above representation is unique if all diagonal elements of A are positive and the upper left-hand elements of Γ_{11} and B_{11} are positive as well (i.e. $\gamma_{11}, \beta_{11} > 0$). Finally, the log-likelihood function for the TVCC-MGARCH model is given by:

$$L(\Theta) = -\frac{K}{2}\log(2\pi) - \frac{1}{2}\log|\Sigma_t| - \frac{1}{2}u'_t\,\Sigma_t^{-1}u_t \tag{9}$$

where Θ is the parameter vector to be estimated, K is the number of variables, and Σ_t is a $K \times K$ conditional variance-covariance matrix. The model is estimated with a Quasi Maximum Likelihood (QML) estimator under the assumption of normality.[8]

[7] Herwartz & Lutkepohl (2000) perform symmetric and asymmetric bivariate BEKK GARCH models. The authors study the relationship between the conditional variances of the variables by impulse response analysis.

6. Results from Bivariate GARCH Analysis

To ensure computational feasibility we employ bivariate TVCC-MGARCH (1,1) models, in which the first variable is always the exchange rate return while the second variable stands for the first difference of the interest rate differential (r), either the stock return (s) or the first log difference of the IP differential (y).[9] For K = 2, Equation (8) can be written as follows:

$$\begin{pmatrix} \sigma_{1,t}^2 & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{2,t}^2 \end{pmatrix} = \begin{pmatrix} a_{11} & 0 \\ a_{12} & a_{22} \end{pmatrix}\begin{pmatrix} a_{11} & a_{12} \\ 0 & a_{22} \end{pmatrix} + \begin{pmatrix} \gamma_{11} & \gamma_{21} \\ \gamma_{12} & \gamma_{22} \end{pmatrix}\begin{pmatrix} u_{1,t-1}^2 & u_{1,t-1}u_{2,t-1} \\ u_{1,t-1}u_{2,t-1} & u_{2,t-1}^2 \end{pmatrix}\begin{pmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{pmatrix}$$

$$+\begin{pmatrix} \beta_{11} & \beta_{21} \\ \beta_{12} & \beta_{22} \end{pmatrix}\begin{pmatrix} \sigma_{1,t-1}^2 & \sigma_{12,t-1} \\ \sigma_{21,t-1} & \sigma_{2,t-1}^2 \end{pmatrix}\begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix}$$

where

$$\sigma_{1,t}^2 = a_{11}^2 + \gamma_{11}u_{1,t-1}^2 + 2\gamma_{11}\gamma_{21}u_{1,t-1}u_{2,t-1} + \gamma_{21}^2u_{2,t-1}^2 + \beta_{11}^2\sigma_{1,t-1}^2 + 2\beta_{11}\beta_{21}\sigma_{21,t-1} + \beta_{21}^2\sigma_{2,t-1}^2 \quad (10)$$

$$\begin{aligned}\sigma_{12,t} &= a_{11}a_{12} + \gamma_{11}\gamma_{12}u_{1,t-1}^2 + \gamma_{11}\gamma_{22}u_{1,t-1}u_{2,t-1} + \gamma_{12}\gamma_{21}u_{1,t-1}u_{2,t-1} + \gamma_{22}\gamma_{21}u_{2,t-1}^2 \\ &+\beta_{11}\beta_{12}\sigma_{1,t-1}^2 + \beta_{12}\beta_{21}\sigma_{21,t-1} + \beta_{11}\beta_{22}\sigma_{12,t-1} + \beta_{22}\beta_{21}\sigma_{2,t-1}^2\end{aligned} \quad (11)$$

$$\begin{aligned}\sigma_{2,t}^2 &= (a_{11}^2 + a_{22}^2) + \gamma_{12}u_{1,t-1}^2 + 2\gamma_{22}\gamma_{12}u_{1,t-1}u_{2,t-1} + \gamma_{22}^2u_{2,t-1}^2 \\ &+\beta_{12}^2\sigma_{1,t-1}^2 + 2\beta_{22}\beta_{12}\sigma_{12,t-1} + \beta_{22}^2\sigma_{2,t-1}^2\end{aligned} \quad (12)$$

Equations (10) and (12) stand for the conditional variance equations, while Equation (11) represents the conditional covariance ($\sigma_{1,2,t}$) which captures the relationship between the two variables. The parameters γ_{11} and γ_{22} illustrate the ARCH effect in the two variables. Namely, these parameters measure the effect of a previous shock on the volatility of the same variable. Similarly, β_{11} and β_{22} are GARCH parameters capturing the degree of volatility persistence in each variable. The short-run dynamic relationships between the variables are captured by γ_{12}, γ_{21}, β_{12}, and β_{21}.

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[8] For a brief discussion of the asymptotic properties of the QML estimator, see Herwartz (2004).

[9] Bivariate TVCC-MGARCH models are estimated using Jmulti econometric software package along with the related book (Lutkepohl & Kratzig, 2004).

Given that the exchange rate return is always treated as the first variable in the bivariate GARCH models, γ_{21} and β_{21} capture spillover effects from another market (i.e. stock market) to the foreign exchange market. The spillover effects in the opposite direction are captured by γ_{12} and β_{12}. Specifically, the coefficient γ_{21} measures the spillover effect of a previous shock in the stock market on the current exchange rate volatility. The coefficient β_{21} measures the spillover effect of the last period's variance in the stock market on the current variance in the forex market.

Along with the bivariate TVCC-MGARCH models we estimate bivariate CCC-MGARCH models to ensure robustness of our analysis. A bivariate CCC-MGARCH (1,1) model is of the following form:

$$\begin{pmatrix} \sigma^2_{1,t} \\ \sigma^2_{2,t} \end{pmatrix} = \begin{pmatrix} a_{11} \\ a_{22} \end{pmatrix} + \begin{pmatrix} \gamma_{11} & 0 \\ 0 & \gamma_{22} \end{pmatrix} \begin{pmatrix} u^2_{1,t-1} \\ u^2_{2,t-1} \end{pmatrix} + \begin{pmatrix} \beta_{11} & 0 \\ 0 & \beta_{22} \end{pmatrix} \begin{pmatrix} \sigma^2_{1,t-1} \\ \sigma^2_{2,t-1} \end{pmatrix}$$

where

$$\sigma^2_{1,t} = a_{11} + \gamma_{11} u^2_{1,t-1} + \beta_{11} \sigma^2_{1,t-1} \quad (13)$$

$$\sigma^2_{2,t} = a_{22} + \gamma_{22} u^2_{2,t-1} + \beta_{22} \sigma^2_{2,t-1} \quad (14)$$

and $\sigma^2_{12,t} = \rho_{12} \sigma_{1,t} \sigma_{2,t}$ (15)

Equations (13) and (14) represent the conditional variance equations, while equation (15) stands for the conditional covariance. Under the assumption of constant conditional correlation the dynamics of the covariance is determined by the dynamics of the two conditional variances. The parameters γ_{11} and γ_{22} illustrate the ARCH effect in the two variables, i.e. the effect of a previous shock on the volatility of the same variable. As in the case of the TVCC-MGARCH (1,1) model, β_{11} and β_{22} are GARCH parameters capturing the degree of volatility persistence in each variable. Given that the CCC-MGARCH (1,1) model does not allow for cross-sectional dynamics across series, the co-movement between the variables is captured by conditional correlations (ρ_{12}), calculated as $\rho_{12} = \sigma_{12,t}^{2} / (\sigma_{1,t}\sigma_{2,t})$.

Below we present the results from the above bivariate GARCH models applied to the cluster of CEE countries (Poland, Hungary, Czech Republic and Slovak Republic) and to the cluster of EMU members (France, Italy, Spain and Ireland).

a. Central and Eastern European Countries

6.2.1. Poland

The main aim is to examine whether other variables export volatility to the exchange rate. Firstly, we examine the dynamic interdependence between the foreign exchange market (represented by exchange rate returns) and the monetary side of the economy (represented by the first difference of the interest rate differential). Under the limits of the CCC-MGARCH (1,1) model the co-movement of the two series is addressed by the estimated conditional correlation. Table 6 (panel A, column 2) shows that the estimate for the conditional correlation between the exchange return and the interest rate differential is statistically insignificant, implying the absence of the co-movement of the variables. In addition, statistical significance of the parameters in the time varying conditional variances is confirmed for γ_{22}, β_{11} and β_{22}.

On the other hand, the properties of the TVCC-MGARCH (1,1) model allow us to investigate possible reciprocal volatility spillover effects. Table 6 (panel B, column 2) shows that the ARCH effect on the interest rate differential (γ_{22}) is significantly different from zero, but the same effect on the exchange rate return (γ_{11}) is statistically insignificant. The diagonal elements of the B matrix imply that volatility in both variables is very persistent.[10] Cross-sectional dynamics exist if the off-diagonal

[10] The estimated coefficients are lower than one, ensuring stationarity in the GARCH process.

elements of the Γ and B matrices are significantly different from zero. Table 6 (panel B, column 2) illustrates that developments in forex markets cannot export volatility to the interest rate differential. On the contrary, γ_{21} and β_{21} coefficients are found to be significant at the 5% level. This implies that previous shocks as well as the last period's variance of the interest rate differential induce changes in exchange rate volatility.

[Insert Table 6 here]

Secondly, we test the hypothesis that significant volatility spillover effects exist between the forex market and the real economic activity. The results from the bivariate CCC-MGARCH (1,1) model, shown in Table 6 (panel A, column 3), confirm the presence of the GARCH effect but we failed to reject the hypothesis of no ARCH effect for both variables. As in the previous case, the results reveal that there is no correlation between the two series.

Table 6 (panel B, column 3) presents the results from the corresponding bivariate TVCC-MGARCH (1,1) model. The diagonal elements of matrix B are statistically significant, quite high, and lower than one, implying high volatility persistence and stationary GARCH processes. In contrast, off-diagonal elements of matrix B are found to be statistically insignificant, thereby implying the absence of a dynamic interrelationship between the two variables. The lack of reciprocal volatility spillover effects is even stronger if we look at the significance of the elements of the Γ matrix. Previous shocks in any variable cannot influence the other variable's variance because in any case off-diagonal elements are not significantly different from zero. Furthermore, there is evidence of own-market effects on the ARCH term only in the forex market. In response to the above hypothesis, the evidence reveals that changes in the IP differentials have no impact on the conditional variance of the exchange rate.

A third task is to investigate whether domestic stock market developments can influence exchange rate volatility.[11] According to the applied bivariate CCC-MGARCH (1,1) model (Table 6, panel A, column 4) all parameters in the time varying conditional variances are statistically significant. This implies that the ARCH and GARCH effects are valid for both variables. In addition, there is evidence of co-movement of the series since the conditional correlation is significantly different from zero.

Although bi-directional spillover effects are considered under the framework of the TVCC-MGARCH (1,1) model, we focus on the impact of shocks in stock markets on changes in the variance of exchange rate returns. Table 6 (panel B, column 4) shows that the coefficients of ARCH and GARCH effects are statistically significant in both equations. In the same column of Table 6, β_{12} and β_{21} coefficients are shown to be statistically insignificant, which implies that the current exchange rate return variance (stock return variance) does not respond to changes in stock return variance (exchange rate return variance). However, there is evidence of significant, but small in magnitude, spillover effect of a previous shock in the stock market on the current exchange rate volatility (γ_{21}=0.044). The spillover effect does not exist in the opposite direction because γ_{12} is not significantly different from zero.

6.2.2. Hungary

Likewise we attempt to examine the bi-directional relations between the exchange rate and the rest of the variables of interest. Although the bivariate CCC-MGARCH (1,1) model presents evidence of significant co-movement of exchange rate returns and stock returns and absence of co-movement in the other two cases,

[11] Kanas (2002) finds that stock return volatility can influence exchange rate volatility for the US, UK, and Japan.

these results should be considered with special caution. In Table 7 (panel A, columns 2-4) the upper left element of matrix Γ (γ_{11}) is statistically significant and negative, which violates the condition of positive definition of the time varying covariance matrix. Furthermore, the condition of stationary GARCH process is violated as well because the diagonal elements of matrix B (β_{11} and $\beta_{22)}$ are statistically significant but higher than one. All these imply that the above models are not well specified and the results are not suitable for deriving valid implications.

Turning to the estimated bivariate TVCC-MGARCH (1,1) models and starting from the relation between the forex market and the monetary-side of the economy, Table 7 (panel B, column 2) illustrates that the ARCH effect is statistically significant only for the interest rate differential. On the other hand, the parameter of the GARCH effect is statistically significant and high for both equations. This is equivalent of the presence of volatility persistent for the forex market and the monetary-side of the economy, with the latter being more persistent. The off diagonal elements of the Γ and B matrices (γ_{12} and β_{12}) which represent the volatility spillover effects from the forex market to the monetary-side of the economy are statistically insignifinant. On the contrary, volatility spillovers in the opposite direction (i.e. from the monetary side to the forex market) are present since the parameters γ_{21} and β_{21} are significantly different from zero.

[Insert Table 7 here]

Next, we present the results from the bivariate TVCC-MGARCH (1,1) model for the relation between the exchange rate return and the IP growth rate differential. Table 7 (panel B, column 3) shows that all elements of the Γ matrix are statistically insignificant. On the other hand, only the diagonal elements of the B matrix are significantly different from zero. This implies that there is evidence of conditional second moment, i.e. GARCH effect, but there is no evidence of volatility spillover effects between the series in any direction. In Table 7 (panel B, column 4) we report the results from the TVCC-MGARCH (1,1) model for the forex market and the stock market. All diagonal elements in B and Γ matrices are statistically significant, thereby implying the existence of ARCH and GARCH effects for both variables. However, there is absence of volatility spillovers between the series in any direction.

6.2.3. Czech Republic

Following the similar estimation procedure we aim to find possible reciprocal spillover effects between the exchange rate and the other variables of interest. The first hypothesis we test is whether the forex market is influenced by monetary developments in the domestic economy and the euro area as a whole. Table 8 (panel A, column 2) presents the existence of the GARCH effect for both variables, while the ARCH effect is valid only for the exchange rate return. The most important outcome is the evidence of co-movement of the two series, which is implied by the statistical significance of the conditional correlation estimate.

While the properties of the CCC-MGARCH (1,1) model do not allow us to capture possible volatility spillovers between the variables, the bivariate specification of the TVCC-MGARCH (1,1) model shows that there is no short-run dynamic interdependence between the exchange rate and the interest rate differential (Table 8, panel B, column 2). In other words, the statistical insignificance of the off-diagonal elements of Γ and B matrices confirms that monetary developments cannot export volatility to the forex market. Similarly, exchange rate volatility cannot induce changes in the interest rate differential. Moreover, the reported results imply the presence of ARCH effect for the interest rate differential and the existence of GARCH effect for the exchange rate return.

[Insert Table 8 here]

The second hypothesis entails the presence of dynamic interdependence between the forex market and the real-side of the economy. Apart from the evidence of ARCH effect (for the exchange rate return) and GARCH effect (for both variables), the bivariate CCC-MGARCH (1,1) model illustrates the lack of significant co-movement of the two series (Table 8, panel A, column 3). Similarly, the TVCC-MGARCH (1,1) model shows that there is no volatility transmission in any case (Table 8, panel B, column 3). This is because all elements in the time varying conditional variances are insignificant apart from the diagonal elements of B matrix (i.e. β_{11} and β_{22}), which measure the volatility persistence of each variable.

Finally, Table 8 (panel A, column 4) reports the results from the CCC-MGARCH (1,1) model for the relation between the forex and the stock markets. The statistical significance of the estimated conditional correlation establishes the co-movement of exchange rate returns and stock returns. In contrast, this relationship is not supported by the results from the corresponding TVCC-MGARCH (1,1) model. Namely, Table 8 (panel B, column 4) shows that all off-diagonal elements of Γ and B matrices are insignificant. Thus, neither the stock market can import volatility to the forex market nor exchange rate volatility can influence stock prices volatility.

6.2.4. Slovak Republic

In the case of Slovak Republic and for the relation between the forex market and the monetary-side of the economy, both biavriate GARCH specification models, i.e. the CCC-MGARCH (1,1) and the TVCC-MGARCH (1,1) models agree that there is no relationship between the exchange rate and the interest rate differential. Starting with the CCC-MGARCH (1,1) model, Table 9 (panel A, column 2) reveals that a previous shock in each variable (exchange rate or interest rate differential) affects the volatility of the same variable. Besides the evidence of the ARCH effect, there is evidence of the GARCH effect only in the exchange rate return equation. Relative to the hypothesis of co-movement of the two series, the estimated conditional correlation is not significantly different from zero. Therefore, there is absence of co-movement of the exchange rate return and the interest rate differential. Similarly, the bivariate TVCC-MGARCH (1,1) model implies no active short-run dynamic interdependence between forex market developments and monetary developments. Table 9 (panel B, column 2) reports that all off diagonal elements of Γ and B matrices are statistically insignificant. In contrast, diagonal elements of Γ matrix (γ_{11} and γ_{22}) and B matrix (β_{11} and β_{22}) are significantly different from zero, thereby establishing the ARCH and GARCH effects for both variables.

[Insert Table 9 here]

Moving on to the examination of the relationship between the exchange rate and the IP differential, Table 9 (panel A, column 3) shows that all parameters in the time varying conditional variances of the bivariate CCC-MGARCH (1,1) model are statistically significant. However, the estimated conditional correlation is not statistically significant, which means the absence of co-movement of the exchange rate and the IP differential. In a similar way, the results from the bivariate TVCC-MGARCH (1,1) model, shown in Table 9 (panel B, column 4), show that the estimated parameters γ_{12}, γ_{21}, β_{12} and β_{21} are not statistically significant. Hence, there is no evidence of volatility transmission from the real-side of the economy to the forex market or vice-versa. While the GARCH effect is established for both variables, the ARCH effect is found to be valid only for the IP differential.

As a final investigation, we model the relationship between exchange rate returns and stock returns. The results from the bivariate CCC-MGARCH (1,1) model, shown in Table 9 (panel A, column 4), show that only the GARCH effect in the stock returns equation is found to be statistically insignificant. All the remaining elements of the time varying conditional variances are significantly different from zero. Unlike the previous relations, there is evidence of co-movement of the two series since the estimated conditional correlation has found to be significantly different from zero. Table 9 (panel B, column 4) also presents the results from the corresponding bivariate TVCC-MGARCH (1,1) model. It is shown that the parameters γ_{22}, β_{11} and β_{22} are significantly different from zero. As a consequence there is evidence of GARCH effect for both variables, while the ARCH effect exists only for the stock returns variable. When it comes to the existence of cross sectional dynamics, all off diagonal elements of Γ and B matrices are statistically insignificant. Therefore, it cannot be concluded that stock market volatility can import volatility to the forex market. Likewise, stock market volatility is not influenced by forex market volatility.

b. Economic and Monetary Union Countries

i. France

Table 10 (panel A, column 2) presents the results of the bivariate CCC-MGARCH (1,1) model for the relation between the exchange rate and the interest rate differential. The only statistical significant elements of the conditional variance matrices are the γ_{11} and β_{11}, which stand for the exchange rate return ARCH and GARCH effect, respectively. The conditional correlation parameter is statistically insignificant, which means that there is no correlation between the series. Panel B (column 2) of the same table shows the results from the corresponding TVCC-MGARCH (1,1) model. All elements of the matrices of the conditional variances, apart from the γ_{12} and β_{21}, are statistically significant.

This evidence provides three implications. First, there is evidence of own-market effects on ARCH and GARCH terms for both variables. Second, while there is no spillover effect of a previous shock in forex market on the current volatility of the interest rate differential (i.e. γ_{12} is insignificant), there is evidence of a significant spillover effect from the exchange rate returns variance to the interest rate differential variance (i.e. β_{12} is significant). The third implication is reverse to the second one. Namely, there is no evidence of spillover effects from the variance of the interest rate differential to the variance of the exchange rate return (i.e. β_{21} is insignificant) but, there is evidence that a previous shock in the interest rate differential can affect the current exchange rate volatility (i.e. γ_{12} is significant). These results have shown that the final implication on the dynamic interdependences between the two series is mixed. However, we can state that the relative importance of the spillover effect from the forex market to the monetary-side of the economy (β_{12} = 7.351) is significantly higher compared to the spillover effect from the monetary-side to the forex market (γ_{21} = 0.004).

[Insert Table 10 here]

In Table 10 (panel A, column 3) all the reported coefficients, apart from the estimated conditional correlation, are statistically significant. Hence, the results from the bivariate CCC-MGARCH (1,1) model reveal the existence of ARCH and GARCH effects for both the exchange rate and the IP differential and the absence of co-movement of the two variables. Similarly, the results from the bivariate TVCC-

MGARCH (1,1) model confirm the existence of the ARCH and GARCH effects for both variables. Panel B (column 3) of Table 10 shows that the off diagonal elements of the Γ matrix are statistically insignificant. In addition, the parameter β_{12} of B matrix is statistically insignificant as well. In combination with the insignificant parameter γ_{12}, this implies that foreign exchange market volatility could not induce changes in the volatility of the IP differential. However, the significant parameter β_{21} implies that exchange rate volatility was influenced by the real-side of the domestic economy and the euro area.

Both the constant conditional correlation (CCC) and the time-varying conditional correlation (TVCC) specifications of the bivariate GARCH (1,1) model find no relationship between exchange rate returns and stock returns. Specifically, the estimated conditional correlation between the two series is statistically insignificant, thereby implying no evidence of co-movement (Table 10, panel A, column 4). Similarly, the TVCC-MGARCH (1,1) model finds no short-run dynamic interdependences between the forex market and the stock market since off diagonal elements of Γ and B matrices are not significantly different from zero (Table 10, panel B, column 4). Finally, the results from the CCC-MGARCH (1,1) model establish the existence of ARCH effect for both variables and the presence of GARCH effect only for the exchange rate return. The TVCC-MGARCH (1,1) model shows that the coefficient of the GARCH effect for both variables is statistically insignificant and high, implying that the variables exhibit volatility persistence.

ii. Italy

By examining the relationship between the forex market and the monetary-side of the economy, we find that all the estimated parameters in the conditional variances of the CCC-MGARCH (1,1) model, apart from the parameter α_{11}, are statistically significant (Table 11, panel A, column 2). Along with the implied evidence of ARCH and GARCH effects for both variables, the statistically significant conditional correlation coefficient (ρ_{11}) confirms the co-movement of the two variables. Similarly, the estimated TVCC-MGARCH (1,1) model establishes the existence of significant ARCH and GARCH effects for the two series. Moreover, Table 11 (panel B, column 2) shows that there are signs of significant interdependence between the variables. Although, the coefficient γ_{12} is statistically insignificant, the high and significant coefficient β_{12} (-1.246) implies a significant spillover effect from the forex market's variance to the variance of the interest rate differential. The estimated coefficients γ_{21} (-0.008) and β_{21} (0.003) are statistically significant, but small. This means that volatility shocks in the monetary-side of the Italian economy and the euro area had a small impact on the forex market volatility.

[Insert Table 11 here]

Next, we investigate the possible relationship between the exchange rate and the IP differential. In this case, the estimated parameters of the conditional variance matrices of the CCC-MGARCH (1,1) model, shown in Table 11 (panel A, column 3), are all statistically significant except the conditional correlation. As before, we have found significant ARCH and GARCH effects for both variables but, there is no evidence of significant correlation between the forex market and the real-side of the economy. The results from the TVCC-MGARCH (1,1) model, which are shown in Table 11 (panel B, column 3), show that the only statistically significant element of the Γ matrix is the γ_{22}. The statistically insignificant coefficient γ_{11} shows that there is no ARCH effect for the exchange rate return, while the insignificant off diagonal elements of matrix (γ_{12} and γ_{21}) imply that there is no spillover effect of a previous shock in one variable on the current volatility of the other variable. In contrast, all coefficients of the B matrix are statistically significant except the γ_{12} coefficient. This evidence implies the presence of a GARCH effect for both variables, the existence of variance spillovers from the real-side to the forex market and absence of variance spillover effects in the opposite direction.

Finally, the estimated CCC-MGARCH (1,1) model for the relation between the forex market and the stock market shows significant ARCH and GARCH effects for both variables and evidence of co-movement of exchange rate returns and stock returns (Table 11, panel A, column 4). In addition, the corresponding estimated TVCC-MGARCH (1,1) model implies significant short-run dynamic interdependences between the two series. Specifically, Table 11 (panel B, column 4) shows that the diagonal elements of Γ matrix (γ_{11} and γ_{22}) are statistically significant, which implies the existence of the ARCH effect for both variables. The diagonal elements of B matrix are statistically significant and high (β_{11}=0.967 and β_{22}=0.941), which implies that the two variables exhibit quite high volatility persistence. When it comes to the cross sectional dynamics, the off diagonal elements of Γ and B matrices, which represent the spillover effect from the stock market to the foreign market (i.e. γ_{21} and β_{21}), are significantly different from zero. However, the spillover effects in the opposite direction are not present since the coefficients γ_{12} and β_{12} are statistically insignificant. This evidence implies that stock market instability has affected exchange rate volatility.

iii. Spain

For the case of Spain, the co-movement of the exchange rate return and the interest rate differential is not supported by the evidence from the estimated CCC-

MGARCH (1,1) model. This is because the conditional correlation coefficient (ρ_{12}) is not statistically significant. In addition, Table 12 (panel A, column 2) shows that the ARCH effect coefficients (γ_{11} and γ_{22}) are statistically significant for both variables, while the GARCH effect coefficient is statistically significant only for the interest rate differential. However, the results from the TVCC-MGARCH (1,1) model imply significant GARCH effect coefficients for both variables, with the exchange rate to exhibit more volatility persistence (Table 12, panel B, column 2). But, both ARCH effect coefficients (γ_{11} and γ_{22}) are found to be statistically insignificant. The off diagonal elements γ_{12} and β_{12}, which represent the spillover effect from the forex market to the interest rate differential, are not significantly different from zero. In contrast, there is evidence of active volatility and variance spillover effects from the monetary-side of the economy to the forex market.

[Insert Table 12 here]

Likewise, we test the relationship between the forex market and the real-side of the economy. The results from the CCC-MGARCH (1,1) model imply absence of co-movement of the exchange rate return and the IP growth differential. Besides the insignificant conditional correlation coefficient (ρ_{12}), Table 12 (panel A, column 3) presents statistically significant ARCH effect coefficients and insignificant GARCH effect coefficients for both variables. In contrast, panel B (column 3) of the same table shows that the TVCC-MGARCH (1,1) model provides evidence of significant GARCH effect coefficients and insignificant ARCH effect coefficients. An interesting outcome is that, in the case of Spain, the IP differential has exhibited low volatility persistence.

However, the off diagonal elements of Γ and B matrices confirm the presence of significant short-run interdependence between the forex market and the real-side of the economy. Specifically, the statistically significant coefficients γ_{21} and β_{21} imply that real output fluctuation in Spain or in the euro area could affect the exchange rate stability. Although, the parameter γ_{12} is found to be statistically insignificant, the significant parameter β_{12} supports the existence of variance spillover effects from the forex market to the real-side of the economy. By comparing the estimated coefficients β_{12} and β_{21}, we observe that the spillover effect from the forex market to the real-side of the economy (β_{12}=1.01) is significantly higher than the spillover effect from the real-side to the forex market (β_{21}=0.051). This evidence highlights the relatively higher importance of the spillover effect from the forex market to the real-side of the economy.

In column 4 of Table 12, we present the results from the CCC-MGARCH (1,1) model (Panel A) and the TVCC-MGARCH (1,1) model (Panel B) for the relation between the forex market and the Spanish stock market. The results from the CCC-MGARCH (1,1) model provide evidence of significant correlation between exchange rate returns and stock returns. The diagonal elements of Γ matrix (γ_{11} and γ_{22}) are statistically significant, which is equivalent of significant ARCH effects for both variables. Nevertheless, this outcome cannot be derived for the GARCH effect as well, because the diagonal elements of B matrix (β_{11} and β_{22}) are not significantly different from zero. In contrast, the estimated diagonal elements of Γ and B matrices of the BEKK specification of the TVCC-MGARCH (1,1) model are significantly different from zero, thereby establishing the presence of ARCH and GARCH effects for both variables. When it comes to the cross sectional dynamics between the variables, there is weak evidence of volatility spillover effect only from the forex market to the stock market.[12] All these imply that stock prices volatility in the Spanish stock market could not affect the Spanish peseta exchange rate vis-à-vis the ECU.

iv. Ireland

Table 13 presents the results from the examination of the dynamic interdependence between the exchange rate and the interest rate differential for the case of Ireland. In Panel A of Table 13, the results from the CCC-MGARCH (1,1) model imply the absence of significant co-movement between exchange rate returns and the rest of the variables. However, these implications cannot be considered as reliable, since the non-negative definition of the Γ and B matrices as well as the stationarity condition of the GARCH processes have been violated.

[Insert Table 13 here]

Given the inappropriate specification of the CCC-MGARCH (1,1) model, we rely only on the results from the TVCC-MGARCH (1,1) model. In the second column of Table 12 (Panel B), we report the results from the investigated relation between the exchange rate and the interest rate differential. All the estimated elements of Γ matrix are shown to be statistically insignificant. One implication from this result is that there is no significant ARCH effect for any variable. A second implication is that there are signs of absence of cross sectional dynamics between the two variables. These signs are even more enforced if we look at the statistically insignificant off diagonal elements of B matrix (β_{12} and β_{21}). The estimated diagonal elements of B matrix are statistically significant and high ($\beta_{11}=\beta_{22}=0.948$), which means that both variables exhibit high volatility persistence. In overall, the results imply no evidence of

[12] This weakness is originated by the insignificant coefficient of β_{12}.

dynamic interdependence between the forex market and the monetary-side of the economy.

Next, we present the results from the relation between the exchange rate return and the IP growth rate differential. In column 3 (Panel B) of Table 13, we can see that all diagonal elements of Γ and B matrices are significantly different from zero. This means that for both variables we have found significant ARCH and GARCH effects. In relation to the evidence from cross-sectional dynamic effects, we have found that changes in the exchange rate could not induce changes in the volatility of the IP differential. In contrast, there is evidence of dynamic dependence between the series in the opposite direction. Although, the coefficient γ_{21} is statistically insignificant, the statistically significant estimate of β_{21} implies evidence of variance spillover effect from the real-side of the economy to the forex market.

Finally, column 4 (Panel B) of Table 13 shows the absence of cross-sectional dynamic effects between the forex market and the stock market in any direction. This is outlined by the insignificant estimates of the off diagonal elements of Γ and B matrices. However, diagonal elements of Γ and B matrices are found to be significantly different from zero, implying the existence of ARCH and GARCH effects for both variables.

7. Conclusion

In this paper we attempt to identify the dynamic relations among the foreign exchange market and the monetary and real sides of the economy as well as the domestic financial sector for the case of four CEE countries and four EMU countries (former EMS members). Preliminary analysis has presented evidence of causal relationships among the variables of interest in most of the examined countries. The most frequently observed relationship is this between the exchange rate and the interest rate differential. Variance decomposition analysis has shown that all variables' forecast error variance is mainly explained by their own innovations, with the exchange rate to be found as the less endogenous variable in almost all VAR systems. However, the cases of France and Ireland are the exceptions of this statement, as the exchange rate seems to be the most endogenous variable in these two VAR models. A highlighted difference between the two clusters of countries (CEE and EMU) is that the importance of the interest rate differential in explaining the exchange rate return's forecast error variance is much higher in the cluster of EMU countries rather than in CEE countries.

Similarly, our main empirical analysis, which is based on the bivariate specification of the CCC-MGARCH (1,1) and TVCC-MGARCH (1,1) models, entails that the presence of active volatility transmission channels between the forex market and the other sectors of the economy ranges from country to country.[13] For the cluster of CEE countries, multivariate GARCH analysis has shown that volatility in the Polish zloty/euro forex market can be influenced by the interest rate differential and the Polish stock market. This finding implies that the sources of exchange rate volatility for this market come from the monetary side of the economy and the financial sector. Similarly, the Hungarian forint/euro forex market can import volatility from the interest rate differential, implying that exchange rate volatility is driven by the monetary side of the economy as well. In contrast, there is no evidence of short-run dynamic relations between the exchange rate and the rest of the variables

[13] Actually, we focus on the results derived from the TVCC-MGARCH (1,1) model for two reasons. First, because the CCC-MGARCH (1,1) model does not allow for cross sectional dynamic relationships, while the TVCC-MGARCH (1,1) model does. Second, Likelihood Ratio (LR) test statistics, constructed using the reported log-likelihood values of the CCC-MGARCH (1,1) and TVCC-MGARCH (1,1) models, imply that the time-varying specification of the MGARCH model should be preferred. LR test statistics are not reported to save space. However, they are available on request by the authors.

for the Czech Republic and Slovakia. This means that any shocks in the real side or the monetary side of the economy as well as in the financial sector do not transmit volatility to the foreign exchange market. In line with the variance decomposition analysis, this finding shows that exchange rate return variance is driven by its own innovations.[14]

A key question is why exchange rate volatility in the Czech Republic and Slovakia is not influenced by other markets' developments. The answer is given by examining the monetary policy and the exchange rate policy vis-à-vis the euro. Both countries apply an inflation targeting regime in which monetary authorities adjust interest rates in a way consistent with exchange rate stability and the convergence criteria. The ECB convergence report (2008) argues that long-term interest rate differentials vis-à-vis the euro area are relatively small in the Czech Republic and Slovakia. Most important is the role of the exchange rate policy. The Czech koruna was pegged to a basket of currencies until early 1996. In 1997 the Czech Republic abandoned the fixed peg exchange rate regime and since then, the Czech koruna has been determined under a managed floating exchange rate regime. This means that although the koruna can fluctuate with respect to the euro, the Central Bank retains the right of intervention in the forex market to smooth excessive fluctuations. Similarly, Slovakia has applied a managed floating regime since October 1998. At this time, Slovakia abandoned the fixed exchange rate regime with a narrow fluctuation band (+/–0.5% to +/–7%) due to the increased pressures on the fixed rate as a result of the Russian currency crisis.

[14] This statement is by and large valid for the forex markets that were found to be sensitive to shocks in other markets. The small absolute value of the estimated coefficients from GARCH models shows that volatility spillover effects are small in magnitude. Namely, most of the current conditional variance is influenced by its last period's variance.

On the other hand, the adoption of a free-floating exchange rate regime in relation with high long-term interest rate differentials (ECB, 2008) can explain the vulnerability of the Polish zloty/euro exchange rate to monetary and financial shocks. Since 2000 the zloty has been determined freely vis-à-vis the euro, indicating high volatility. During the period 1991–2001, the Hungarian forint was determined under a crawling peg exchange rate regime. Since September 2001, this regime has been replaced by a fixed central parity against the euro (282.36 forint per euro), while the fluctuation band has been extended from +/–2.5% to +/–15%. However, domestic economic imbalances that are reflected in high long-term interest rate differentials against euro rates (ECB, 2008) can explain the relatively high volatility of the forint exchange rate against the euro as well as its vulnerability to monetary shocks.

As for the cluster of EMU countries, the results reveal bi-directional volatility spillover effects between the exchange rate and the interest rate differential for the cases of France and Italy. Although this finding implies that exchange rate volatility had been influenced by the monetary side of the economy, the truth is that forex market developments had caused higher influence to interest rates. In addition, it is found that exchange rate variance had been affected by the variance of the IP differential. Hence, we have found that exchange rate volatility, for France and Italy during the pre-EMU period, came from the monetary side as well as the real side of the economy.

For the case of Spain, we have found the existence of volatility transmission channels from the interest rate differential to the exchange rate and from the exchange rate to the stock market. Moreover, there is evidence of reciprocal volatility spillover effects between the exchange rate and the IP differential. These results describe the argument that forex market developments in Spain had been influenced by monetary and real factors. Finally, the results from the Irish case reveal that exchange rate volatility had been driven only by the real side of the economy.

Moving on to policy implications, this empirical analysis informs policy makers in CEE countries that monetary instability provokes exchange rate volatility. So, by stabilizing the monetary side of the economy, monetary authorities can reduce the degree of exchange rate exposure to excess volatility. Furthermore, the evidence that monetary shocks are more important than real shocks in affecting exchange rate volatility sheds light on the effectiveness of the applied exchange rate policy vis-à-vis the euro. According to theory, if monetary shocks are more important, a fixed regime is appropriate. In contrast, if real shocks drive the exchange rate developments then a free-floating exchange rate regime seems to be appropriate. Therefore, the adoption of a managed-floating regime with a relatively narrow fluctuation band, as adopted by the majority of the CEE countries, is consistent with the information derived from this analysis.

Moreover, the results indicate that the exchange rates in CEE countries, which have been found to be influenced by other market developments, have the same source of volatility (i.e. monetary shocks). This means that a common monetary policy could treat exchange rate volatility, thereby showing that the foregoing participation of those countries in EMU is not expected to produce asymmetric shocks in the monetary side of the euro area.[15]

On the contrary, exchange rates vis-à-vis the ECU were driven by monetary and real shocks for France, Italy and Spain and only by real shocks for the case of Ireland. The fact that real shocks are important determinants of exchange rate fluctuation, during the pre-EMU period, implies that the fixed exchange rate regime, under the

[15] We remind that Slovakia has already joined the EMU.

framework of the Exchange Rate Mechanism (ERM) I, was not the appropriate. Since most of the examined period (1980-1998) covers the EMS era (1979-1993), we can state that this finding could be one of the reasons of the EMS crisis. Namely, our results show that EU was not ready for a monetary union, at least in the form of the EMS, since the fixed exchange rate regime was not consistent with the macroeconomic developments in EU members.[16]

Aknowledgements

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[16] It is important to note that this analysis neither implies that EMU is not an efficient monetary union nor that it currently faces asymmetric shocks. We can only argue that the role of real shocks in exchange rate volatility can explain, among others, the EMS crisis.

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Figure 1: Poland

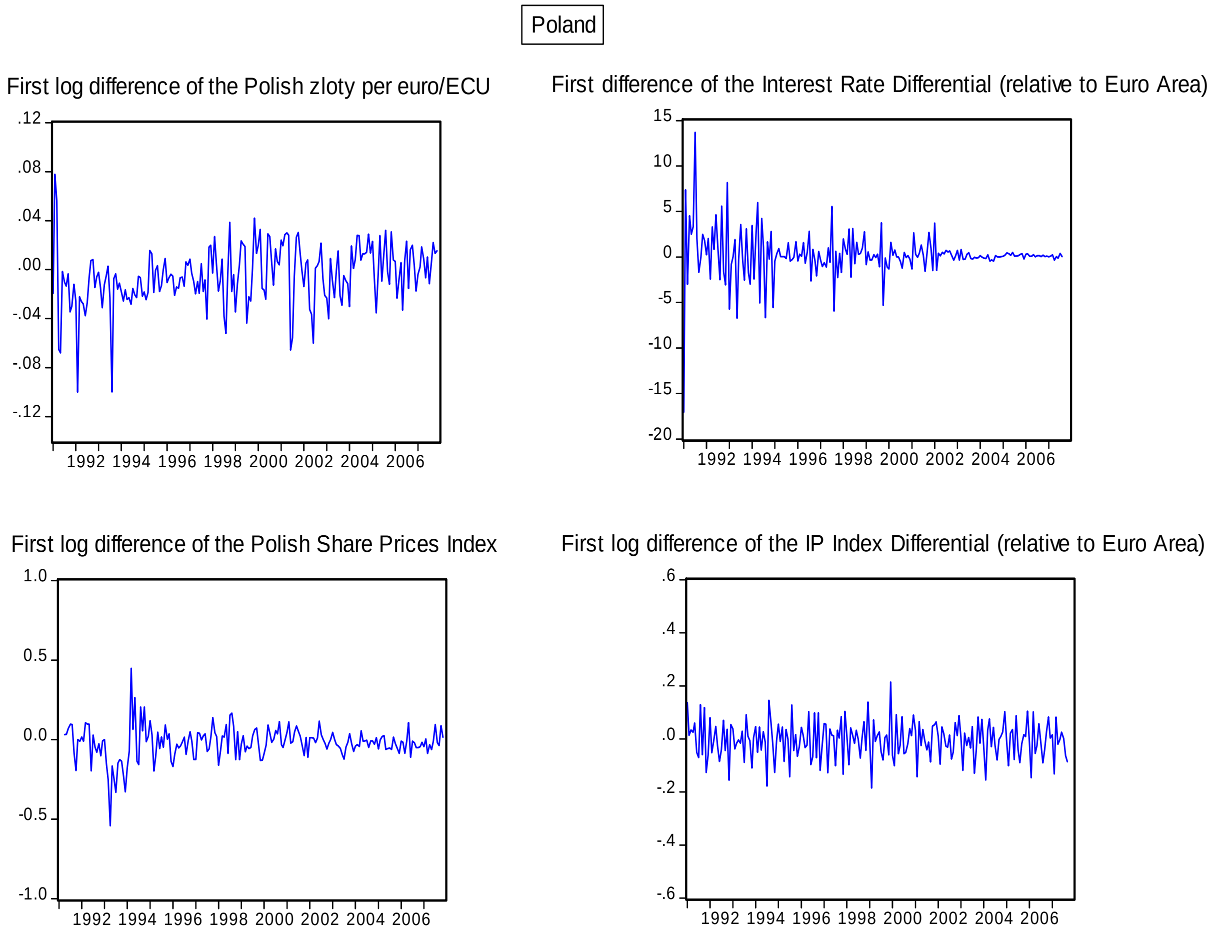


Figure 2: Hungary

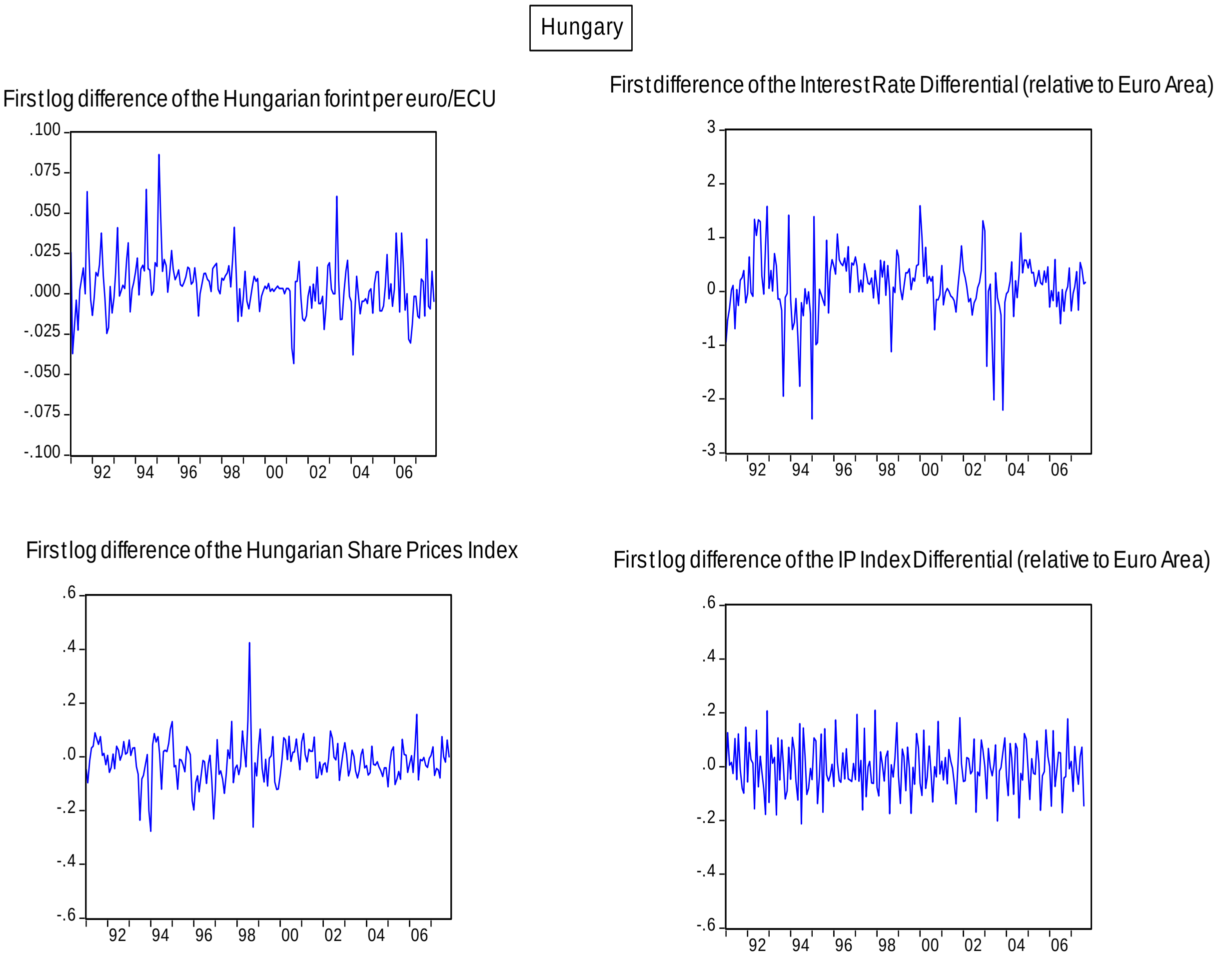


Figure 3: Czech Republic

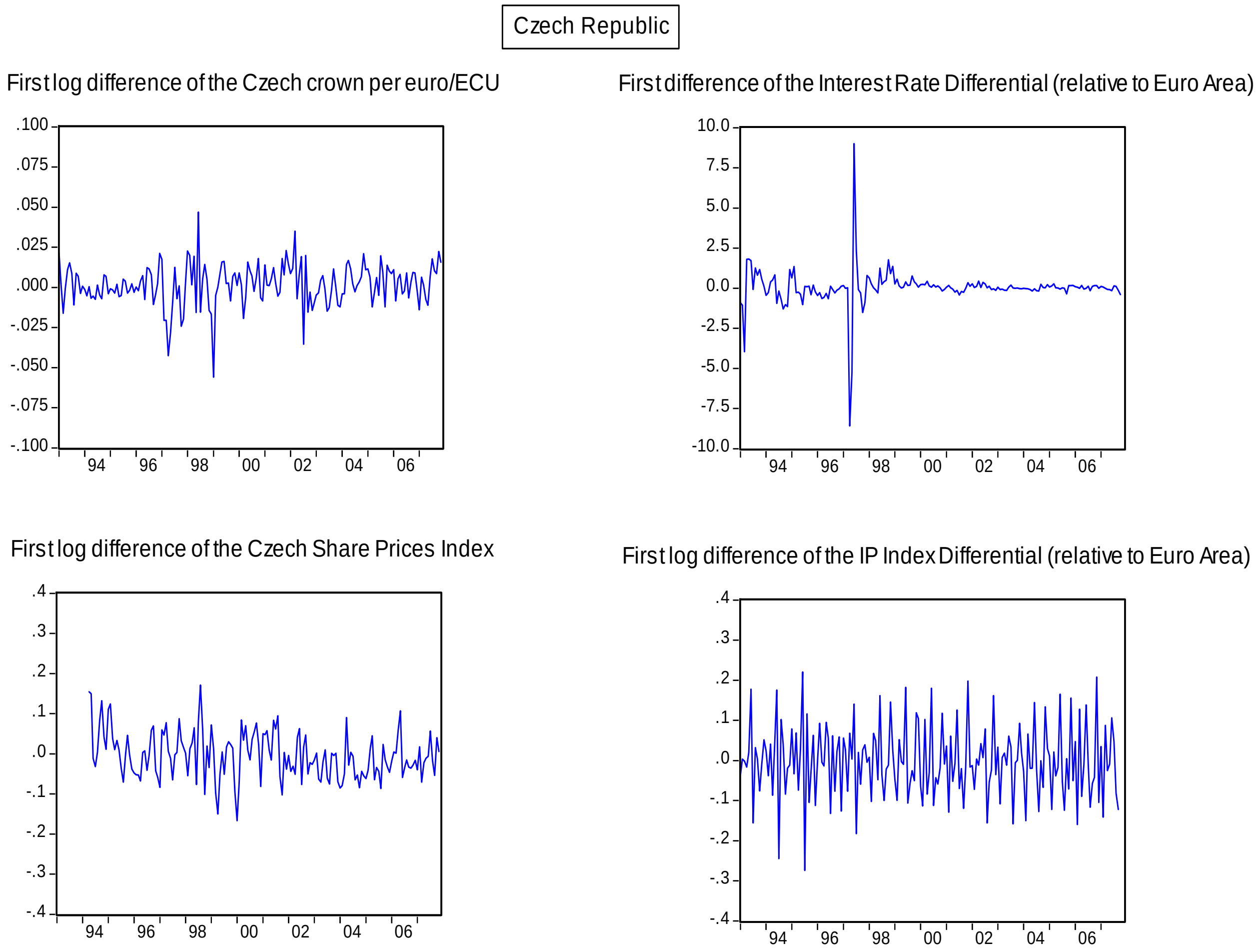


Figure 4: Slovak Republic

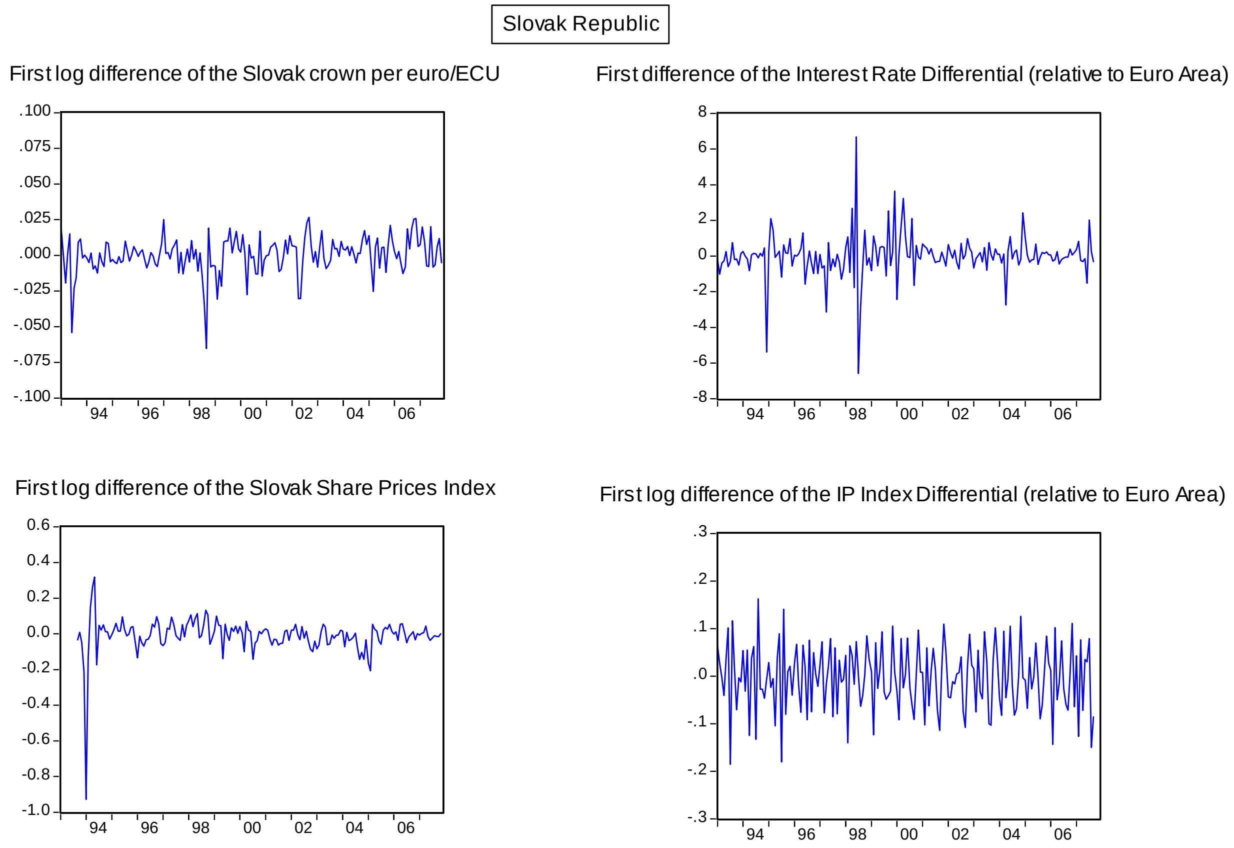


Figure 5: France

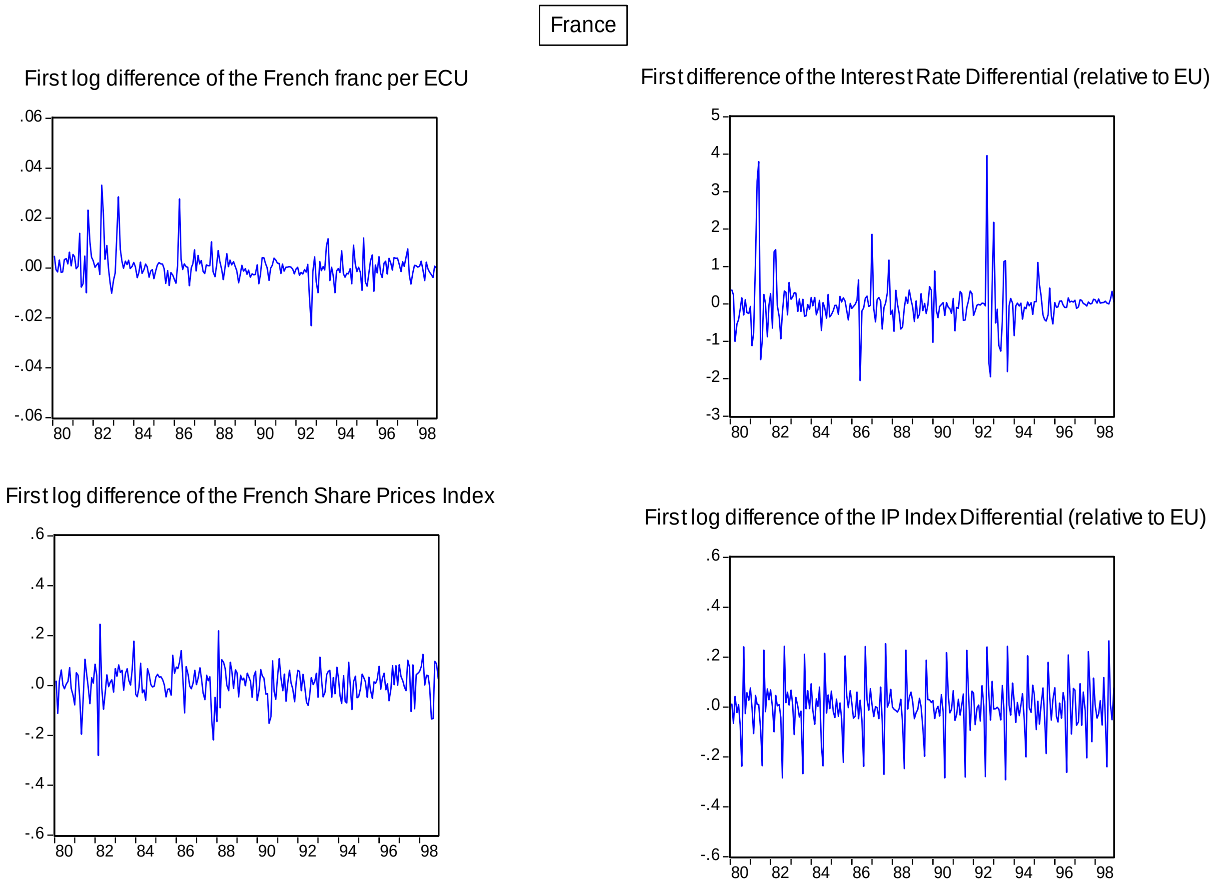


Figure 6: Italy

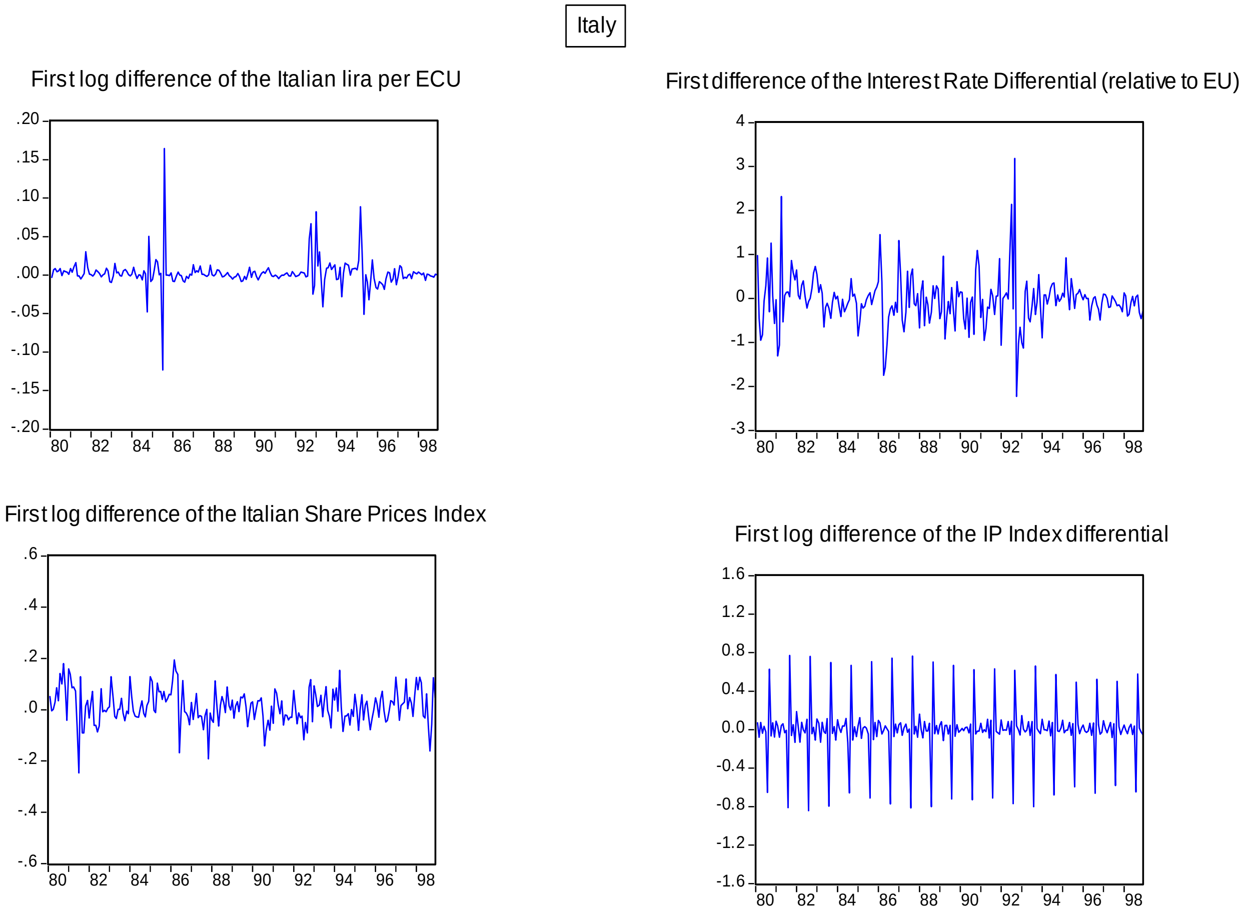
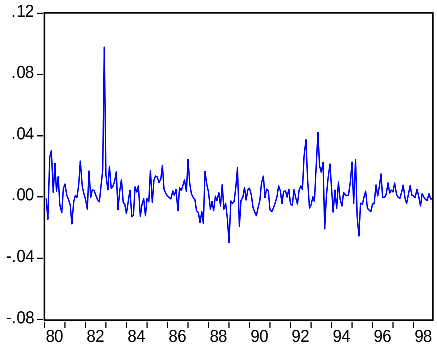


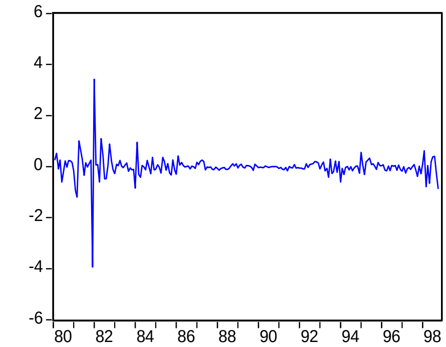
Figure 7: Spain

Spain

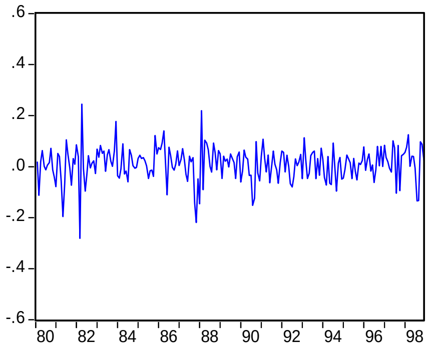
First log difference of the Spanish peseta per ECU



First difference of the Interest Rate Differential (relative to EU)



First log difference of the Spanish Share Prices Index



First log difference of the IP index Differential (relative to EU)

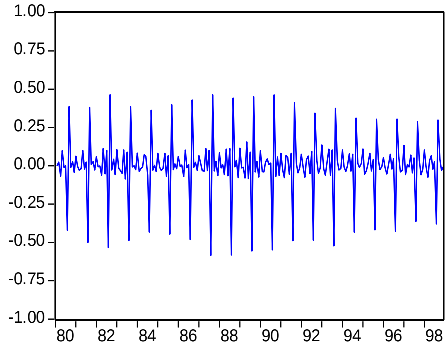


Figure 8: Ireland

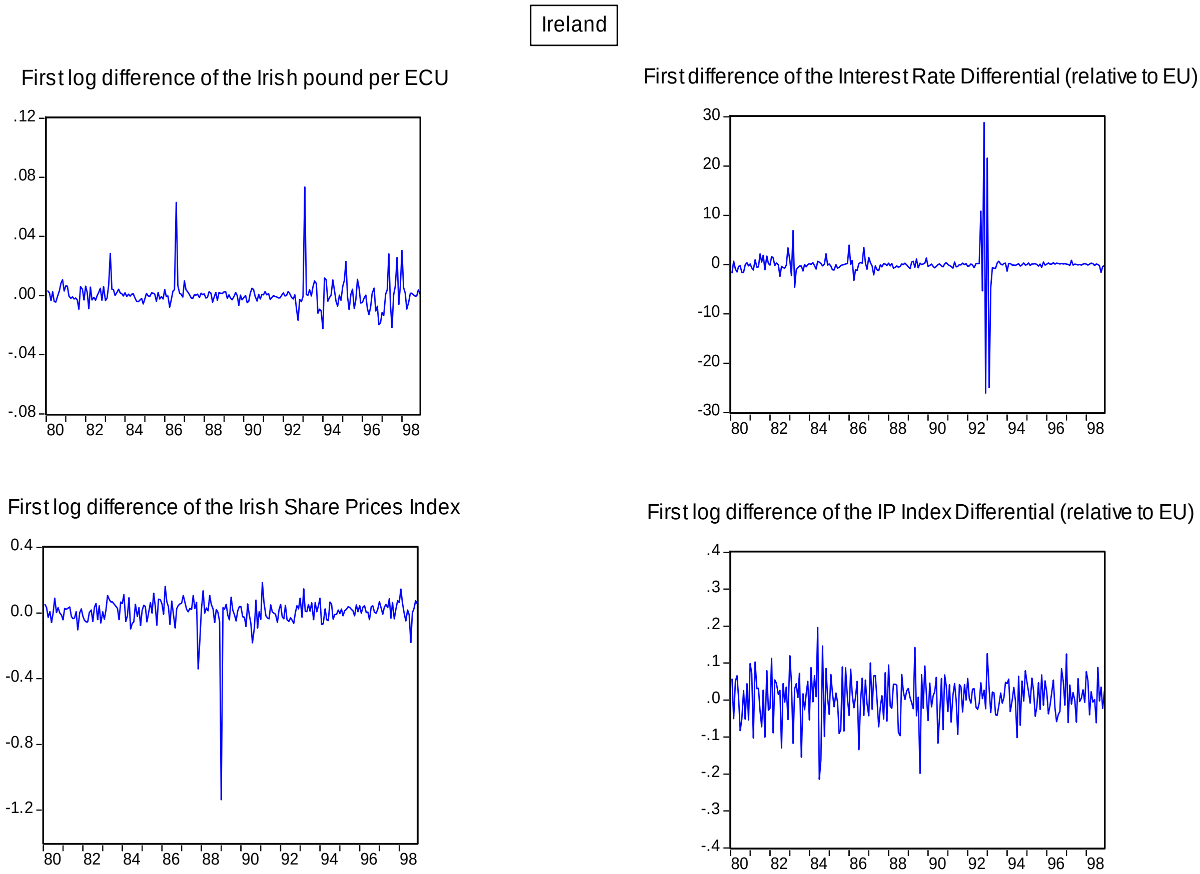


Table 1: Preliminary Statistics (CEE Countries)

	Poland				Hungary				Czech Republic				Slovak Republic			
	e	s	r	y	e	s	r	y	e	s	r	y	e	s	r	y
Mean (μ)	-0.005	-0.02	0.208	-0.004	0.004	-0.015	0.101	-0.004	0.001	-0.003	0.003	-0.002	0.0002	-0.008	0.009	-0.003
Standard Deviation (σ)	0.023	0.1	2.567	0.069	0.017	0.076	0.598	0.09	0.012	0.058	1.185	0.089	0.012	0.098	1.214	0.067
μ/σ	-0.217	-0.200	0.081	-0.058	0.235	-0.197	0.169	-0.044	0.083	-0.052	0.003	-0.022	0.017	-0.082	0.007	-0.045
Skewness	-0.518	-0.428	-0.75	-0.096	0.884	0.4	-0.914	0.055	-0.58	0.35	-0.314	0.086	-1.313	-4.637	-0.28	-0.185
Kurtosis	5.247	8.73	16.76	2.989	6.647	8.83	6.398	2.601	5.86	3.24	37.801	3.12	7.755	42.217	14.395	2.632
Jargue-Bera	51.82^{n}	279.95^{n}	1596^{n}	0.31	139.3^{n}	293.8^{n}	124.7^{n}	1.42	71.15^{n}	3.76	8985.5^{n}	0.327	220.2^{n}	14543^{n}	960.04^{n}	2.007
(probability)	(0.00)	(0.00)	(0.00)	(0.85)	(0.00)	(0.00)	(0.00)	(0.49)	(0.00)	(0.15)	(0.00)	(0.84)	(0.00)	(0.00)	(0.00)	(0.36)
ADF statistic	-11.46*	-4.17*	-5.86*	-3.66*	-9.35*	-4.227*	-5.579*	-4.92*	-5.008*	-9.06*	-8.93*	-2.56**	-10.18*	-9.028*	-16.58*	-1.91***
(probability)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.05)

Notes:

1. e stands for the first log difference of the nominal exchange rate per euro; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the Euro Area's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the Euro Area's IP index).
2. μ/σ is a measure of relative dispersion, calculated as the mean divided by the standard deviation.
3. P-values of accepting the null hypothesis are shown in parentheses.
4. n denotes that normality is rejected at any significance level.
5. * , ** and *** denote rejection of the null of a unit root at the 1%, 5% and 10% significance levels, respectively.

Table 2: Preliminary Statistics (EMU Countries)

	France				Italy				Spain				Ireland			
	e	s	r	y	e	s	r	y	e	s	r	y	e	s	r	y
Mean (μ)	0.000	0.009	-0.011	0.000	0.002	0.013	-0.036	0.000	0.002	0.009	-0.012	0.001	0.001	0.006	-0.051	0.006
Standard Deviation (σ)	0.006	0.066	0.655	0.109	0.020	0.066	0.582	0.289	0.012	0.067	0.443	0.188	0.009	0.097	3.630	0.061
μ/σ	0.000	0.141	-0.017	0.000	0.115	0.192	-0.062	0.000	0.208	0.140	-0.028	0.003	0.075	0.062	-0.014	0.099
Skewness	1.587	-0.561	2.447	-0.269	2.101	-0.129	0.914	-0.36	2.496	-0.529	-1.029	-0.702	3.706	-7.423	0.229	-0.454
Kurtosis	12.124	5.620	16.740	4.203	33.201	3.942	9.152	5.865	20.148	5.428	44.742	5.697	28.350	86.553	45.474	4.028
Jargue-Bera (probability)	867.17^{n} (0.00)	75.47^{n} (0.00)	1976.6^{n} (0.00)	16.13^{n} (0.00)	8794.1^{n} (0.00)	9.02^{n} (0.01)	389.5^{n} (0.00)	82.56^{n} (0.00)	2990.3^{n} (0.00)	65.75^{n} (0.00)	16374.4^{n} (0.00)	86.66^{n} (0.00)	6597.7^{n} (0.00)	6811.8^{n} (0.00)	17065.5^{n} (0.00)	17.80^{n} (0.00)
ADF statistic	-11.66*	-14.63*	-13.43*	-3.562*	-17.629*	-11.05*	-13.74*	-3.638*	-10.86*	-14.87*	-13.42*	-4.28*	-12.42*	-13.81*	-10.23*	-3.769*
(probability)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Notes:

1. e stands for the first log difference of the nominal exchange rate per ECU; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the EU interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the EU IP index).
2. μ/σ is a measure of relative dispersion, calculated as the mean divided by the standard deviation.
3. P-values of accepting the null hypothesis are shown in parentheses.
4. n denotes that normality is rejected at any significance level.
5. * , ** and *** denote rejection of the null of a unit root at the 1%, 5% and 10% significance levels, respectively.

Table 3: Granger causality test (CEE Countries)

Null Hypothesis	Poland	Hungary	Czech Republic	Slovak Republic
	F-statistic (probability)			
r does not Granger cause e	7.008* (0.00)	0.42 (0.83)	1.73 (0.16)	5.24* (0.00)
e does not Granger cause r	0.25 (0.61)	2.73** (0.02)	0.69 (0.55)	0.54 (0.64)
s does not Granger cause e	0.80 (0.37)	0.38 (0.86)	0.44 (0.72)	0.07 (0.97)
e does not Granger cause s	0.04 (0.89)	1.86 (0.10)	3.93* (0.00)	0.76 (0.51)
y does not Granger cause e	0.06 (0.79)	0.59 (0.70)	0.08 (0.96)	0.24 (0.86)
e does not Granger cause y	4.43** (0.03)	0.90 (0.47)	0.23 (0.87)	3.73** (0.01)
s does not Granger cause r	11.82* (0.00)	2.04*** (0.07)	0.89 (0.44)	0.05 (0.98)
r does not Granger cause s	6.10** (0.01)	0.81 (0.53)	0.16 (0.92)	0.62 (0.59)
y does not Granger cause r	0.00 (0.97)	0.45 (0.81)	0.18 (0.90)	0.50 (0.67)
r does not Granger cause y	0.01 (0.90)	1.10 (0.35)	0.60 (0.61)	0.77 (0.50)
y does not Granger cause s	0.06 (0.80)	1.23 (0.29)	0.49 (0.69)	0.07 (0.97)
s does not Granger cause y	0.17 (0.67)	0.51 (0.76)	0.09 (0.96)	2.19*** (0.09)

Notes:

1. e stands for the first log difference of the nominal exchange rate per euro; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the Euro Area's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the Euro Area's IP index).
2. P-values of accepting the null hypothesis are shown in parentheses.
3. * , ** and *** denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

Table 4: Granger causality test (EMU Countries)

Null Hypothesis	France	Italy	Spain	Ireland
	F-statistic (probability)			
r does not Granger cause e	7.436* (0.00)	0.631 (0.53)	5.915* (0.00)	16.71* (0.00)
e does not Granger cause r	0.722 (0.48)	0.610 (0.54)	1.554 (0.21)	21.16* (0.00)
s does not Granger cause e	3.478** (0.03)	0.659 (0.52)	0.383 (0.68)	0.783 (0.46)
e does not Granger cause s	0.605 (0.54)	0.619 (0.54)	3.01*** (0.05)	0.485 (0.62)
y does not Granger cause e	0.563 (0.57)	0.004 (1.00)	0.075 (0.93)	1.173 (0.31)
e does not Granger cause y	0.660 (0.51)	2.989*** (0.05)	0.173 (0.84)	0.253 (0.78)
s does not Granger cause r	0.902 (0.41)	3.708** (0.03)	1.992 (0.14)	0.779 (0.46)
r does not Granger cause s	0.110 (0.89)	0.593 (0.55)	4.311** (0.01)	1.066 (0.35)
y does not Granger cause r	0.400 (0.67)	0.665 (0.52)	0.248 (0.78)	0.641 (0.53)
r does not Granger cause y	2.185 (0.11)	0.228 (0.80)	0.001 (1.00)	0.297 (0.74)
y does not Granger cause s	7.436* (0.00)	0.916 (0.40)	0.115 (0.89)	0.201 (0.82)
s does not Granger cause y	0.722 (0.48)	0.819 (0.44)	1.227 (0.30)	0.057 (0.94)

Notes:

1. e stands for the first log difference of the nominal exchange rate per ECU; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the EU interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the EU IP index).
2. P-values of accepting the null hypothesis are shown in parentheses.
3. * , ** and *** denote rejection of the null hypothesis at the 1%, 5% and 10% significance levels, respectively.

Table 5a: Variance Decomposition (Poland)

Variance Decomposition of (10-period forecast horizon)	Explained by Innovations of (in percentage)			
	e	**r**	**s**	**y**
e	97.52	1.26	1.10	0.09
r	2.82	91.24	5.03	0.88
s	2.43	2.03	95.06	0.46
y	2.11	1.93	0.53	95.40

Table 5b: Variance Decomposition (Hungary)

Variance Decomposition of (10-period forecast horizon)	Explained by Innovations of (in percentage)			
	e	**r**	**s**	**y**
e	97.99	0.63	0.70	0.66
r	5.00	92.73	1.50	0.75
s	6.09	1.61	91.03	1.25
y	0.52	0.56	3.12	95.78

Table 5c: Variance Decomposition (Czech Republic)

Variance Decomposition of (10-period forecast horizon)	Explained by Innovations of (in percentage)			
	e	**r**	**s**	**y**
e	98.25	1.44	0.16	0.13
r	4.77	94.54	0.45	0.21
s	6.83	0.41	92.18	0.56
y	1.68	1.82	0.31	96.17

Table 5d: Variance Decomposition (Slovak Republic)

Variance Decomposition of (10-period forecast horizon)	Explained by Innovations of (in percentage)			
	e	**r**	**s**	**y**
e	97.77	2.04	0.14	0.04
r	2.32	97.25	0.07	0.34
s	2.70	0.73	96.37	0.18
y	4.35	1.80	1.38	92.44

Table 5e: Variance Decomposition (France)

Variance Decomposition of (10-period forecast horizon)	Explained by Innovations of (in percentage)			
	e	**r**	**s**	**y**
e	79.80	15.85	3.05	1.30
r	5.90	86.67	6.48	0.96
s	3.92	7.68	87.48	0.92
y	4.63	2.95	6.14	86.28

Table 5f: Variance Decomposition (Italy)

Variance Decomposition of (10-period forecast horizon)	Explained by Innovations of (in percentage)			
	e	**r**	**s**	**y**
e	92.46	5.41	1.66	0.46
r	3.48	87.26	9.10	0.16
s	5.81	6.63	86.42	1.14
y	5.68	3.05	6.15	85.12

Table 5g: Variance Decomposition (Spain)

Variance Decomposition of (10-period forecast horizon)	Explained by Innovations of (in percentage)			
	e	**r**	**s**	**y**
e	92.09	4.80	1.49	1.62
r	3.82	89.30	3.59	3.28
s	5.76	13.16	79.83	1.25
y	4.28	10.84	2.68	82.20

Table 5h: Variance Decomposition (Ireland)

Variance Decomposition of (10-period forecast horizon)	Explained by Innovations of (in percentage)			
	e	**r**	**s**	**y**
e	79.75	17.23	0.72	2.30
r	5.11	93.36	0.65	0.88
s	2.59	1.21	93.54	2.66
y	4.60	3.49	6.42	85.49

Note:
e stands for the first log difference of the nominal exchange rate per euro/ECU; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the Euro Area's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the Euro Area's IP index).

Table 6: Bivariate GARCH results: POLAND

Parameter	Variable 1 = e Variable 2 = r	Variable 1 = e Variable 2 = y	Variable 1 = e Variable 2 = s
Panel A: Constant Conditional Correlation (Bollerslev model)			
α_{11}	0.000 (0.866)	0.000 (0.882)	0.000* (6.081)
α_{22}	0.004 (0.763)	0.001 (1.291)	0.000 (1.568)
γ_{11}	0.056 (1.039)	0.055 (1.026)	0.460* (3.075)
γ_{22}	0.482* (3.317)	-0.049 (-1.562)	0.278*** (1.822)
β_{11}	0.895* (9.310)	0.895* (9.318)	0.088* (2.731)
β_{22}	0.652* (13.694)	0.913* (10.786)	0.718* (6.748)
ρ_{12}	-0.057 (-0.985)	-0.002 (0.035)	-0.229* (-3.266)
Log-Likelihood	142.574	731.739	708.130
Panel B: Time-Varying Conditional Correlation (BEKK model)			
α_{11}	0.00127 (0.0001)	0.009 (0.65)	0.015* (3.59)
α_{12}	0.0442 (0.0001)	0.014 (0.20)	0.028** (2.50)
α_{22}	0.573 (0.017)	0.006 (0.03)	0.012*** (1.91)
γ_{11}	0.2193 (0.04)	0.25** (2.00)	0.46* (4.02)
γ_{12}	-0.037 (-0.002)	0.055 (0.14)	-0.14 (-0.44)
γ_{21}	0.029** (2.26)	-0.042 (-0.56)	0.044* (3.13)
γ_{22}	0.223* (8.07)	0.13 (1.12)	0.33* (4.20)
β_{11}	0.948* (4.45)	0.87* (4.87)	0.62* (3.13)
β_{12}	0.03 (0.43)	-0.05 (-0.17)	0.617 (1.08)
β_{21}	-0.002* (-3.54)	0.059 (0.51)	0.003 (0.17)
β_{22}	0.948* (4.58)	0.96* (7.03)	0.88* (13.87)
Log-Likelihood	555.816	695.900	688.021

Notes:

1. e stands for the first log difference of the nominal exchange rate per euro; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the Euro Area's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the Euro Area's IP index).
2. $\alpha_{11,}$ α_{12} and α_{22} are constant terms of the variance equations.
3. γ_{11} and γ_{22} represent the ARCH effect in the two variables, respectively.
4. β_{11} and β_{22} show the GARCH terms, which measure volatility persistence of each series.
5. γ_{12} measures the spillover effect of a previous shock in variable 1 on the current volatility of variable 2. γ_{21} measures the spillover effect in the opposite direction.
6. β_{12} measures the spillover effect of the last period's variance of variable 1 on the current variance of variable 2. β_{21} measures the spillover effect in the opposite direction.
7. ρ_{12} represents the conditional correlation between the two series.
8. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively.
9. Robust t-statistics are shown in parentheses.

Table 7: Bivariate GARCH results: HUNGARY

Panel A: Constant Conditional Correlation (Bollerslev model)			
Parameter	Variable 1 = e Variable 2 = r	Variable 1 = e Variable 2 = y	Variable 1 = e Variable 2 = s
α_{11}	0.000*** (1.710)	0.000*** (1.75)	0.000* (3.285)
α_{22}	0.019** (2.426)	0.001 (0.392)	0.003* (5.009)
γ_{11}	-0.079* (-6.186)	-0.079* (-6.671)	-0.089* (-5.267)
γ_{22}	0.128* (3.036)	-0.023 (-0.341)	0.421* (4.507)
β_{11}	1.045* (83.834)	1.042* (86.182)	1.057* (70.416)
β_{22}	0.824* (17.971)	0.865** (2.304)	0.105 (1.009)
ρ_{12}	-0.052 (-0.523)	-0.043 (-0.511)	0.358* (5.461)
Log-Likelihood	369.164	726.204	818.945
Panel B: Time-Varying Conditional Correlation (BEKK model)			
α_{11}	0.004 (0.609)	0.012* (3.05)	0.006** (2.38)
α_{12}	0.028 (0.159)	0.008 (0.10)	0.016 (1.49)
α_{22}	0.134* (3.66)	0.0002 (0.0001)	0.004 (0.27)
γ_{11}	0.068 (0.59)	0.002 (0.04)	0.257** (2.20)
γ_{12}	-0.274 (-0.126)	-0.24 (-0.22)	0.184 (0.33)
γ_{21}	-0.011* (-3.84)	0.011 (0.08)	-0.007 (-0.28)
γ_{22}	0.201* (3.11)	0.17 (0.63)	0.17*** (1.86)
β_{11}	0.892* (12.90)	0.85* (5.08)	0.91* (13.77)
β_{12}	-2.18 (-1.17)	-0.003 (-0.3)	-0.30 (-1.05)
β_{21}	0.008* (4.05)	0.02 (0.43)	0.0009 (0.10)
β_{22}	0.945* (28.05)	0.99* (3.90)	0.95* (29.57)
Log-Likelihood	273.307	556.332	632.362

Notes:
1. e stands for the first log difference of the nominal exchange rate per euro; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the Euro Area's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the Euro Area's IP index).
2. $\alpha_{11,}$ α_{12} and α_{22} are constant terms of the variance equations.
3. γ_{11} and γ_{22} represent the ARCH effect in the two variables, respectively.
4. β_{11} and β_{22} show the GARCH terms, which measure volatility persistence of each series.
5. γ_{12} measures the spillover effect of a previous shock in variable 1 on the current volatility of variable 2. γ_{21} measures the spillover effect in the opposite direction.
6. β_{12} measures the spillover effect of the last period's variance of variable 1 on the current variance of variable 2. β_{21} measures the spillover effect in the opposite direction.
7. ρ_{12} represents the conditional correlation between the two series.
8. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively.
9. Robust t-statistics are shown in parentheses.

Table 8: Bivariate GARCH results: CZECH REPUBLIC

Panel A: Constant Conditional Correlation (Bollerslev model)			
Parameter	Variable 1 = e Variable 2 = r	Variable 1 = e Variable 2 = y	Variable 1 = e Variable 2 = s
α_{11}	0.000 (1.330)	0.000 (1.167)	0.000 (1.212)
α_{22}	0.786 (1.326)	0.001 (0.804)	0.002* (4.297)
γ_{11}	0.199* (2.948)	0.238* (2.836)	0.233* (2.944)
γ_{22}	0.576 (1.092)	-0.026 (-0.655)	0.500* (3.677)
β_{11}	0.789* (12.603)	0.768* (11.699)	0.785* (13.326)
β_{22}	0.086* (3.645)	0.870* (4.930)	0.083 (1.026)
ρ_{12}	0.253* (3.057)	-0.060 (-0.783)	-0.233* (-3.143)
Log-Likelihood	314.596	719.118	743.862
Panel B: Time-Varying Conditional Correlation (BEKK model)			
α_{11}	0.024* (2.96)	0.001 (0.03)	0.0003 (0.008)
α_{12}	0.618 (1.60)	0.01 (0.02)	0.004 (0.007)
α_{22}	0.205 (1.04)	0.014 (0.01)	0.014 (0.09)
γ_{11}	0.66 (0.86)	0.2 (0.54)	0.22 (1.39)
γ_{12}	-1.31 (-0.06)	-0.06 (-0.09)	-0.06 (-0.18)
γ_{21}	-0.0055 (-1.36)	-0.03 (-0.43)	-0.03 (-0.69)
γ_{22}	0.357*** (1.64)	0.2 (1.60)	0.22** (2.04)
β_{11}	0.558*** (1.67)	0.95* (20.73)	0.96** (2.25)
β_{12}	8.52 (0.74)	-0.02 (-0.18)	-0.04 (-0.29)
β_{21}	0.0168 (1.60)	0.03 (0.77)	0.028 (1.22)
β_{22}	0.561 (1.05)	0.94* (13.36)	0.93** (2.002)
Log-Likelihood	158.752	550.155	682.309

Notes:

1. e stands for the first log difference of the nominal exchange rate per euro; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the Euro Area's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the Euro Area's IP index).
2. α_{11}, α_{12} and α_{22} are constant terms of the variance equations.
3. γ_{11} and γ_{22} represent the ARCH effect in the two variables, respectively.
4. β_{11} and β_{22} show the GARCH terms, which measure volatility persistence of each series.
5. γ_{12} measures the spillover effect of a previous shock in variable 1 on the current volatility of variable 2. γ_{21} measures the spillover effect in the opposite direction.
6. β_{12} measures the spillover effect of the last period's variance of variable 1 on the current variance of variable 2. β_{21} measures the spillover effect in the opposite direction.
7. ρ_{12} represents the conditional correlation between the two series.
8. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively.
9. Robust t-statistics are shown in parentheses.

Table 9: Bivariate GARCH results: SLOVAK REPUBLIC

Panel A: Constant Conditional Correlation (Bollerslev model)			
Parameter	Variable 1 = e Variable 2 = r	Variable 1 = e Variable 2 = y	Variable 1 = e Variable 2 = s
α_{11}	0.000** (2.308)	0.000** (2.363)	0.000** (2.024)
α_{22}	0.454 (1.486)	0.007* (8.941)	0.002* (3.929)
γ_{11}	0.455** (2.397)	0.472** (2.443)	0.336*** (1.844)
γ_{22}	0.511*** (1.702)	0.215* (5.722)	1.096** (2.335)
β_{11}	0.486* (3.862)	0.472* (3.776)	0.567* (3.560)
β_{22}	0.275 (1.070)	0.799* (8.059)	0.001 (0.038)
ρ_{12}	0.058 (0.928)	-0.008 (-0.099)	-0.188* (-2.780)
Log-Likelihood	280.572	767.858	764.375
Panel B: Time-Varying Conditional Correlation (BEKK model)			
α_{11}	0.055* (10.47)	0.001 (0.12)	0.002 (0.77)
α_{12}	0.372* (5.50)	0.01** (2.30)	0.022 (0.94)
α_{22}	0.0024 (0.00)	0.009*** (1.85)	0.001 (0.003)
γ_{11}	0.109** (2.34)	0.21 (1.00)	0.008 (0.02)
γ_{12}	-0.739 (-0.36)	0.06 (0.13)	0.04 (0.04)
γ_{21}	-0.0046 (-0.60)	0.03 (0.54)	0.008 (0.57)
γ_{22}	0.28** (2.04)	0.21*** (1.67)	0.27* (4.48)
β_{11}	0.643* (5.15)	0.95* (23.17)	0.96* (28.15)
β_{12}	-6.70 (1.02)	0.02 (0.19)	-0.17 (-0.64)
β_{21}	-0.0002 (-0.01)	-0.03 (-1.03)	-0.014 (-1.53)
β_{22}	0.86** (2.05)	0.94* (11.47)	0.90* (15.13)
Log-Likelihood	15.666	664.047	658.995

Notes:

1. e stands for the first log difference of the nominal exchange rate per euro; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the Euro Area's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to the Euro Area's IP index).
2. α_{11}, α_{12} and α_{22} are constant terms of the variance equations.
3. γ_{11} and γ_{22} represent the ARCH effect in the two variables, respectively.
4. β_{11} and β_{22} show the GARCH terms, which measure volatility persistence of each series.
5. γ_{12} measures the spillover effect of a previous shock in variable 1 on the current volatility of variable 2. γ_{21} measures the spillover effect in the opposite direction.
6. β_{12} measures the spillover effect of the last period's variance of variable 1 on the current variance of variable 2. β_{21} measures the spillover effect in the opposite direction.
7. ρ_{12} represents the conditional correlation between the two series.
8. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively.
9. Robust t-statistics are shown in parentheses.

Table 10: Bivariate GARCH results: FRANCE

Panel A: Constant Conditional Correlation (Bollerslev model)			
Parameter	Variable 1 = e Variable 2 = r	Variable 1 = e Variable 2 = y	Variable 1 = e Variable 2 = s
α_{11}	0.000 (0.964)	0.000* (4.398)	0.000 (0.963)
α_{22}	0.189 (1.349)	0.002* (6.247)	0.002** (2.564)
γ_{11}	0.222*** (1.654)	0.220* (5.041)	0.222*** (1.652)
γ_{22}	0.448 (1.455)	-0.134* (-6.207)	0.260** (2.078)
β_{11}	0.766* (5.621)	0.765* (30.513)	0.766* (5.608)
β_{22}	0.142 (0.600)	0.975* (109.87)	0.267 (1.170)
ρ_{12}	-0.003 (-0.017)	-0.089 (-1.115)	0.000 (0.003)
Log-Likelihood	673.492	1064.862	1169.428
Panel B: Time-Varying Conditional Correlation (BEKK model)			
α_{11}	0.014* (13.055)	0.0002* (3.161)	0.0002 (0.471)
α_{12}	-0.182* (-3.01)	-0.001* (-6.181)	-0.005 (-0.786)
α_{22}	0.112* (2.648)	0.023* (4.813)	0.014 (0.924)
γ_{11}	0.726* (4.933)	0.178** (2.348)	0.201 (0.224)
γ_{12}	10.376 (0.756)	0.142 (0.632)	-0.07 (-0.029)
γ_{21}	0.004* (3.335)	0.024 (1.207)	-0.031 (-0.814)
γ_{22}	0.235** (2.31)	0.235* (4.4)	0.224 (1.514)
β_{11}	0.734* (48.516)	0.961* (143.5)	0.951* (13.237)
β_{12}	7.351* (3.411)	0.041 (1.215)	-0.026 (-0.137)
β_{21}	-0.001 (-1.546)	-0.044* (-4.767)	0.028 (1.401)
β_{22}	0.87* (25.032)	0.937* (58.71)	0.943* (12.605)
Log-Likelihood	443.219	744.136	951.54

Notes:

1. e stands for the first log difference of the nominal exchange rate per ECU; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the EU's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to EU IP index).
2. $\alpha_{11,}$ α_{12} and α_{22} are constant terms of the variance equations.
3. γ_{11} and γ_{22} represent the ARCH effect in the two variables, respectively.
4. β_{11} and β_{22} show the GARCH terms, which measure volatility persistence of each series.
5. γ_{12} measures the spillover effect of a previous shock in variable 1 on the current volatility of variable 2. γ_{21} measures the spillover effect in the opposite direction.
6. β_{12} measures the spillover effect of the last period's variance of variable 1 on the current variance of variable 2. β_{21} measures the spillover effect in the opposite direction.
7. ρ_{12} represents the conditional correlation between the two series.
8. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively.
9. Robust t-statistics are shown in parentheses.

Table 11: Bivariate GARCH results: ITALY

Panel A: Constant Conditional Correlation (Bollerslev model)			
Parameter	Variable 1 = e Variable 2 = r	Variable 1 = e Variable 2 = y	Variable 1 = e Variable 2 = s
α_{11}	0.000 (1.038)	0.000* (10.794)	0.000 (1.051)
α_{22}	0.025** (1.962)	0.013* (4.596)	0.001 (1.607)
γ_{11}	0.490*** (1.828)	0.452* (6.638)	0.496*** (1.706)
γ_{22}	0.343** (2.239)	-0.092* (-9.664)	0.185** (2.486)
β_{11}	0.682* (5.601)	0.686* (37.738)	0.676* (5.249)
β_{22}	0.617* (5.001)	0.938* (29.883)	0.523** (2.385)
ρ_{12}	0.199** (1.957)	0.087 (0.750)	-0.139** (-2.118)
Log-Likelihood	501.089	628.775	956.336
Panel B: Time-Varying Conditional Correlation (BEKK model)			
α_{11}	0.006 (1.632)	0.003* (6.322)	0.001 (0.462)
α_{12}	0.235* (5.428)	0.058* (4.953)	0.007 (0.702)
α_{22}	0.031* (4.796)	0.041* (2.895)	0.013* (2.602)
γ_{11}	0.413** (2.555)	0.177 (1.223)	0.188* (6.165)
γ_{12}	-0.298 (-0.34)	0.097 (0.264)	0.234 (1.569)
γ_{21}	-0.008* (-2.787)	0.027 (1.607)	0.035** (2.344)
γ_{22}	0.413* (6.182)	0.225* (6.103)	0.212* (4.109)
β_{11}	0.934* (36.772)	0.951* (40.567)	0.967* (49.295)
β_{12}	-1.246** (-2.561)	0.031 (1.296)	-0.006 (-0.11)
β_{21}	0.003* (3.435)	-0.027* (-8.239)	-0.025** (-2.533)
β_{22}	0.824* (26.399)	0.949* (97.325)	0.941* (33.428)
Log-Likelihood	395.007	254.019	861.125

Notes:

1. e stands for the first log difference of the nominal exchange rate per ECU; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the EU's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to EU IP index).
2. $\alpha_{11,}$ α_{12} and α_{22} are constant terms of the variance equations.
3. γ_{11} and γ_{22} represent the ARCH effect in the two variables, respectively.
4. β_{11} and β_{22} show the GARCH terms, which measure volatility persistence of each series.
5. γ_{12} measures the spillover effect of a previous shock in variable 1 on the current volatility of variable 2. γ_{21} measures the spillover effect in the opposite direction.
6. β_{12} measures the spillover effect of the last period's variance of variable 1 on the current variance of variable 2. β_{21} measures the spillover effect in the opposite direction.
7. ρ_{12} represents the conditional correlation between the two series.
8. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively.
9. Robust t-statistics are shown in parentheses.

Table 12: Bivariate GARCH results: SPAIN

Panel A: Constant Conditional Correlation (Bollerslev model)			
Parameter	Variable 1 = e Variable 2 = r	Variable 1 = e Variable 2 = y	Variable 1 = e Variable 2 = s
α_{11}	0.000* (4.379)	0.000* (4.394)	0.000* (4.349)
α_{22}	0.000 (0.000)	0.035* (6.548)	0.002** (2.551)
γ_{11}	1.260* (2.813)	1.284* (2.907)	1.271* (2.878)
γ_{22}	0.308* (3.920)	0.468* (6.286)	0.257** (2.044)
β_{11}	0.090 (1.488)	0.091 (1.543)	0.096 (1.551)
β_{22}	0.808* (19.700)	0.860 (1.259)	0.249 (1.057)
ρ_{12}	0.002 (0.029)	0.047 (0.813)	-0.137*** (-1.964)
Log-Likelihood	718.203	839.323	1029.488
Panel B: Time-Varying Conditional Correlation (BEKK model)			
α_{11}	0.007 (0.114)	0.007* (3.263)	0.002* (2.648)
α_{12}	-0.078** (-2.562)	-0.196* (-5.606)	0.028* (5.635)
α_{22}	0.064* (5.886)	0.032* (5.954)	0.003** (2.546)
γ_{11}	0.341 (0.643)	0.024 (0.758)	0.366* (3.141)
γ_{12}	0.884 (0.26)	0.539 (0.991)	0.501*** (1.766)
γ_{21}	0.014*** (1.861)	0.026** (2.459)	-0.055 (-0.523)
γ_{22}	0.261* (4.686)	0.629** (2.312)	0.409* (4.631)
β_{11}	0.982 (58.681)	0.887* (60.767)	0.889* (23.567)
β_{12}	0.141 (1.407)	1.01* (5.498)	0.153 (0.477)
β_{21}	-0.015* (-5.858)	0.051* ((39.555)	-0.046 (-1.27)
β_{22}	0.912* (47.11)	0.113* (6.447)	0.8* (15.125)
Log-Likelihood	306.245	650.452	987.284

Notes:

1. e stands for the first log difference of the nominal exchange rate per ECU; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the EU's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to EU IP index).
2. $\alpha_{11,}$ α_{12} and α_{22} are constant terms of the variance equations.
3. γ_{11} and γ_{22} represent the ARCH effect in the two variables, respectively.
4. β_{11} and β_{22} show the GARCH terms, which measure volatility persistence of each series.
5. γ_{12} measures the spillover effect of a previous shock in variable 1 on the current volatility of variable 2. γ_{21} measures the spillover effect in the opposite direction.
6. β_{12} measures the spillover effect of the last period's variance of variable 1 on the current variance of variable 2. β_{21} measures the spillover effect in the opposite direction.
7. ρ_{12} represents the conditional correlation between the two series.
8. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively.
9. Robust t-statistics are shown in parentheses.

Table 13: Bivariate GARCH results: IRELAND

Panel A: Constant Conditional Correlation (Bollerslev model)			
Parameter	Variable 1 = e Variable 2 = r	Variable 1 = e Variable 2 = y	Variable 1 = e Variable 2 = s
α_{11}	0.000 (-0.866)	0.000 (-0.842)	0.000* (6.467)
α_{22}	0.981* (10.61)	0.004* (5.16)	0.000* (-3.497)
γ_{11}	-0.018* (-25.75)	-0.018* (-24.82)	-0.015* (-7.539)
γ_{22}	0.831* (3.872)	0.206** (2.036)	-0.010* (-36.844)
β_{11}	1.054* (149.69)	1.053* (151.01)	1.010* (221.648)
β_{22}	0.106 (1.225)	-0.307 (-1.469)	1.043* (212.621)
ρ_{12}	-0.011 (-0.148)	-0.040 (-0.567)	0.064 (1.031)
Log-Likelihood	391.889	1105.415	1041.735
Panel B: Time-Varying Conditional Correlation (BEKK model)			
α_{11}	0.021 (0.031)	0.(5)9*** (1.76)	0.00001 (0.064)
α_{12}	-0.189 (-0.368)	-0.(4)9* (-4.656)	-0.022 (-1.376)
α_{22}	0.787 (0.346)	0.014* (2.777)	0.013 (1.516)
γ_{11}	0.224 (0.322)	0.178*** (1.65)	0.152*** (1.873)
γ_{12}	0.027 (0.006)	-0.118 (-0.381)	-0.096 (-0.401)
γ_{21}	-0.029 (-1.453)	-0.037 (-1.773)	-0.032 (-0.233)
γ_{22}	0.223 (0.923)	0.223* (4.551)	0.233* (2.531)
β_{11}	0.948* (114.449)	0.959* (45.727)	0.961* (13.959)
β_{12}	-0.029 (-0.2)	-0.027 (-0.538)	-0.029 (-0.175)
β_{21}	0.029 (1.439)	0.029* (3.311)	0.028 (0.713)
β_{22}	0.948* (36.165)	0.938* (35.059)	0.934* (8.888)
Log-Likelihood	691.565	960.269	743.331

Notes:

1. e stands for the first log difference of the nominal exchange rate per ECU; s stands for the first log difference of the national share price index; r stands for the first difference of the interest rate differential (national interest rate relative to the EU's interest rate); y stands for the first log difference of the IP index differential (national IP index relative to EU IP index).
2. $\alpha_{11,}$ α_{12} and α_{22} are constant terms of the variance equations.
3. γ_{11} and γ_{22} represent the ARCH effect in the two variables, respectively.
4. β_{11} and β_{22} show the GARCH terms, which measure volatility persistence of each series.
5. γ_{12} measures the spillover effect of a previous shock in variable 1 on the current volatility of variable 2. γ_{21} measures the spillover effect in the opposite direction.
6. β_{12} measures the spillover effect of the last period's variance of variable 1 on the current variance of variable 2. β_{21} measures the spillover effect in the opposite direction.
7. ρ_{12} represents the conditional correlation between the two series.
8. *, ** and *** denote statistical significance at the 1%, 5% and 10% level, respectively.
9. Robust t-statistics are shown in parentheses.