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Exchange Rate Co-movements, Hedging and Volatility Spillovers in New EU Forex Markets

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Exchange Rate Co-movements, Hedging and Volatility Spillovers in New EU Forex Markets

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Abstract:
We analyze time-varying exchange rate co-movements and volatility spillovers between the Czech koruna, the Polish zloty, the Hungarian forint and the dollar/euro from 1999 to 2016. We apply the dynamic conditional correlations (DCC) model and the Diebold Yilmaz spillover index to examine the periods prior to and during the GFC, plus during and after the EU debt crisis. We found declining conditional correlations between new EU exchange rates prior to both crises. During the GFC and the European debt crisis, the correlations reach the lowest level, and increase afterwards. Based on the DCC model results we calculate portfolio weights and hedge ratios. We show that during both crises portfolio diversification benefits increase but hedging costs rise as well. Based on the spillover index we document that during calm periods most of the volatilities are due to each currency's own history. However, during the distress periods volatility spillovers among currencies increase substantially.

Keywords: Exchange rate, New EU forex markets, volatility, DCC model, volatility spillover index, EU debt crisis, global financial crisis
JEL: C52, F31, F36, G15, P59

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1. Introduction, motivation and related literature

We analyze recent dynamics of the dependency and connectedness on the forex markets in several new member states of the European Union (EU). There is established evidence that developed and emerging forex markets are interdependent and integrated (Kitamura, 2010; Diebold and Yilmaz, 2015; Greenwood-Nimmo et al., 2016). Despite of the above evidence, the new EU forex markets remain outside the research mainstream, even though the currencies of the Czech Republic, Hungary, and Poland score highly in terms of their attractiveness to risk-capital investors (Groh and von Liechtenstein, 2009). Further, these currencies are important for diversifying the portfolios of mutual and hedge funds, which are primarily domiciled in developed markets (Jotikasthira et al., 2012).[1] We aim to fill a gap in the literature: we analyze time-varying co-movements and volatility spillovers of the three new EU forex markets, along with computing hedge ratios and portfolio weights for these currencies.

The European forex market underwent a fundamental change when the euro became a joint currency for euro-area members in 1999. Its introduction also altered the relative importance and nature of interdependencies among major world currencies on the global forex market (Antonakakis, 2012). Emerging European forex markets became part of the global forex landscape once the currencies of these emerging economies gradually became freely tradable during the 1990s. The currencies of the Czech Republic, Hungary, and Poland have gained further importance as those countries were becoming more integrated into the EU economy after their 2004 accession (Hanousek and Kočenda, 2011). For the countries that joined the EU in 2004 and later, euro adoption became a future goal.

Both developed and emerging forex markets experienced another important change: on September 15, 2008 the collapse of US investment bank Lehman Brothers brought volatility and distress to the financial markets followed by a credit crunch. Financial contagion spread from the USA and it was soon followed by the European debt crisis. Both the global financial crisis (GFC) and the debt crisis in Europe (EU

[1] According to Jotikasthira et al. (2012), new EU markets are important for the portfolio diversification of mutual and hedge funds domiciled mainly in developed markets. They find 270 active funds in the Czech Republic, 276 funds in Poland, and 295 funds in Hungary following the crisis. More importantly, these fund holdings account for 3.6% of the float-adjusted market capitalization in the Czech Republic, 8.6% in Hungary and 4.7% in Poland; this represents more than 2.6% the average value of free-float market capitalization found in 25 emerging markets examined by Jotikasthira et al. (2012).

debt crisis) renewed interest in the nature of contagion effects among financial markets (Aloui et al., 2011).

In this paper, we build on the above evidence and analyze the extent and evolution of interdependencies and connectedness on the new EU forex markets. Based on the Dynamic Conditional Correlation (DCC) model developed by Engle (2002), we analyze the degrees and dynamics of co-movements among currencies. The assessment of time variations in the correlations between different assets has critical inference for asset allocation and risk management because weak market linkages offer potential gains from international diversification (Singh et al., 2010).[2] Furthermore, we use conditional variances and covariances estimated from the DCC model to compute hedge ratios and portfolio weights of individual currencies in an optimal portfolio. Our results may help foreign investors recognize whether new EU countries should be treated as whole or whether it is preferential to select assets individually from each country to improve portfolio diversification.

Through a complementary analysis, we examine the extent and nature of volatility spillovers in new EU forex markets. This is performed because volatility and its spillovers across currencies affect decisions about hedging open forex positions and may exacerbate nonsystematic risk that diminishes the gains from international portfolio diversification (Kanas, 2001). We analyze volatility spillovers using a generalized version of Diebold and Yilmaz's (2012) spillover index (DY index).

Our analysis is performed on daily data from 1999 to 2016. The span of our dataset begins with the introduction of the euro and covers both periods of relatively calm development and periods of distress. For this reason, the data are divided into four subsamples. The first sample covers the period prior to the GFC (1999-2008), the second reflects the GFC itself (2008-2010) and the third covers the European debt crisis (2010-2012). The last portion of the data reflects the period during which both crises were subdued (2012-2016).

To the best of our knowledge, our analysis represents the first comprehensive assessment of interdependencies and risk spillovers on new EU forex markets. We find that conditional correlations between new EU exchange rates and the USD/EUR

[2] It is established evidence that correlations between markets increase during volatile periods (Ang and Chen, 2002) and decrease in bull markets (Ang and Bekaert, 2002, Longin and Solnik, 2001). Such asymmetry is explained via the leverage effect (Black, 1976) and volatility feedback effect (Wu, 2001).

tend to decrease prior to the GFC and the EU debt crises. Once economic and financial disturbances decay, the correlations begin to rise to pre-crisis levels. Consequently, our results indicate that hedging during the GFC and the EU debt crisis cost more than before and after the crisis. Volatility and interdependencies on the new EU forex markets is assessed via spillovers. Most of the time, own-currency volatilities explain substantial share of exchange rates movements. On the other hand, volatility spillovers between currencies considerably increase during the GFC, and this also leads to an increase in the total volatility spillover index. The Hungarian forint is the dominant currency in the volatility transmission in each examined period.

The remainder of this paper is organized as follows. Section 2 provides a literature review. Section 3 describes our data, methodology and hypothesis. Section 4 presents the empirical results and their economic implications, and Section 5 concludes.

2. Literature review

The level of volatility in the financial market is the source of many important investors' decisions. For example, it may affect investors' willingness to hold risky assets. It can also influence companies' investment plans and banks' ability to lend money. Exchange rate volatility affects import and exporter prices uncertainty and thus has an impact on international trade flows (Rose, 2000). Baum et al. (2001) show that exchange rate volatility has an impact on the multinational companies' profitability and consequently on the stock prices of these companies. It also has an adverse effect on industrial production and employment (Belke and Gros, 2002).

Volatility has become the subject of broad research since Bollerslav (1986) and Taylor (1986) introduced their generalized autoregressive conditional heteroscedastic (GARCH) model. Later, Bollerslev's Constant Conditional Correlations (CCC) model was expanded by Engle (2002), who introduced the Dynamic Conditional Correlation (DCC) model. The DCC model allows modeling dynamic time-varying correlations between time series. In applications, Adrian and Brunnermeier (2016) demonstrate that multivariate GARCH models can help capture the dynamic of systematic risk. DeMiguel et al. (2009) state that time-varying movements can increase the performance of optimal asset allocation.

Diebold and Yilmaz (2009, 2012) advanced volatility research by introducing the spillover index (DY index). This index is based on forecast error variance decomposition from vector autoregressions (VARs) and measures the degree and direction of volatility transmission between financial markets. This new approach has quickly been adopted in the literature. Kumar (2013) examines volatility spillovers between exchange rates and stock prices in India, Brazil, and South Africa. He discovers a bi-directional relationship between stock and forex markets, in terms of both returns and volatility spillovers. Antonakakis and Kizys (2015) analyze volatility transmission between commodities and major forex pairs. They confirm the existence of dynamic linkages between commodity and forex markets. Fujiwara and Takahashi (2012) estimate the DY index to gauge the degree of interaction in both financial markets and real economic activity among Asian economies.

In the literature, numerous studies have examined co-movements and volatility spillovers in forex markets. However, most of them focus on developed markets. For example, Inagaki (2007) examines the connectedness between the British pound and the euro. His findings support unidirectional volatility spillover from the euro to the British pound. Nikkinen et al. (2006) examine linkages in expected future volatilities among major European currencies. They show that implied volatility of the euro significantly affects the volatility expectations of the British pound and the Swiss franc. McMillan and Speight (2010) analyze interdependencies and volatility spillovers in the U.S. dollar, Japanese yen and British pound. They claim that news affecting the U.S. dollar account for as much as 30% of the movement in sterling and yen returns. Boero et al. (2011) analyze dependence structures between the euro, the British pound, the Swiss franc and the Japanese yen via the copula model. They show the marked tendency of the Swiss franc to follow the fluctuations in the euro. Finally, Bekiros and Marcellino (2013) employ wavelet analyses to forecast FX rate co-movements.

Emerging markets, and especially new EU exchange rates, are under-researched. To the best of our knowledge, Bubák et al. (2011) are the only researchers to analyze the dynamics of volatility transmission to, from and among the Czech, Hungarian and Polish currencies, together with the U.S., dollar for the period of 2003-2009. They find that each new EU currency is characterized by a different volatility transmission pattern. Pramor and Tamirisa (2006) examine volatility trends in the

Central and Eastern European currencies. Their results suggest that these trends are closely correlated, although to a lesser degree than the major European currencies prior to the introduction of the euro. Andrieş et al. (2016) investigate exchange rates in Central and Eastern European countries via a wavelet analysis. They find a high degree of co-movements in short-term fluctuations among the exchange rates of the Czech Republic, Poland and Hungary.

3. Data, methodology and hypotheses

3.1 Dataset

Our dataset contains daily exchange rates of the currencies of three new EU member states against the euro: the Czech koruna (CZK/EUR), the Polish zloty (PLN/EUR), and the Hungarian forint (HUF/EUR). We also use exchange rate series of the US dollar against the euro (USD/EUR).[3] The exchange rates are expressed in terms of direct quotes as the amount x of a quoting currency i that one needs to buy one unit of euro (base or reference currency). For example, when we refer to the (exchange rate of the) Czech koruna, we refer to its value defined as the number of korunas required to buy one euro. The time span runs from January 1, 1999 to December 30, 2016 and contains 4,610 observations. Data are quoted at 2:15 p.m. (C.E.T). Time series were downloaded from the ECB online database.

Daily exchange rates are transformed into daily percentage log returns (r_t) defined as: $r_t = \ln(s_t - s_{t-1}) * 100$, where s_t is the daily closing exchange rate at time t. Via the Augmented Dickey-Fuller (ADF) GLS test, the returns are shown to be stationary (see Appendix, Table A1). A negative change in an exchange rate means that the amount of quoting currency i needed to buy one unit of the euro decreases, denoting an appreciation of a quoting currency i with respect to the euro. Similarly, a positive change denotes a depreciation of the quoting currency.

The beginning of the sample corresponds to the day on which the euro came into existence as an accounting currency. The dataset includes daily data from 1999 to 2016 and is divided into four subsamples to capture effects of financial distress. The first sample covers the period prior to the GFC (January 1, 1999-September 14,

[3] In the other words, we examine conditional correlations between new EU currencies and the U.S. dollar. The U.S. dollar has been the dominant international currency since World War II. It is the world's dominant vehicle currency, representing 88% of all trade in 2016 (BIS, 2016). Our analysis of new EU forex rates co-movements and spillovers with the U.S. dollar eliminates the effect of euro fluctuations. Therefore, the results regarding diversification strategies and hedging costs could be beneficial for international investors whose portfolios are denominated in the U.S. dollar.

2008), the second represents the key impact of the GFC (September 15, 2008-April 30, 2010) and the third covers the EU debt crisis (May 3, 2010-July 26, 2012). The fourth subsample captures the period following the EU debt crisis (July 27, 2012-December 30, 2016).

We follow Frankel and Saravelos (2012) and link the beginning of the GFC to the bankruptcy of Lehman Brothers on September 15, 2008. The starting point of the EU debt financial crisis corresponds to May 3, 2010, when the IMF, the ECB and the European Commission announced a 110 billion euros three-year aid package designed to rescue Greece (Hanousek et al., 2014). The period following May 2010 is characterized by a rise in the bond yields of heavily indebted Eurozone countries in anticipation of the emergence of problems similar to those in Greece. Moreover, an increase in global risk aversion during this period resulted in a fall in equity returns in advanced countries, particularly in the financial sector (Stracca, 2015). The end of the EU debt crisis coincides with a remarkable statement by the ECB President Mario Draghi (2012) at the Global Investment Conference in London on July 26, 2012: "Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough". Fiordelisi and Ricci (2016) show that the European financial markets started to rally immediately after this statement and that the economic situation began to improve as well.[4] The rest of the data cover the post-EU debt crisis period.[5]

3.2. Dynamic Conditional Correlation GARCH (DCC-GARCH)

We use the DCC model of Engle (2002) to assess the evolution of co-movements between new EU countries' exchange rates and the USD/EUR. Using this model, we determine whether the dynamic correlation between exchange rates increases, decreases or is stable over the time. The DCC model offers several advantages relative to simple correlation analysis. First, it is parsimonious compared to many multivariate GARCH models.[6] Second, the DCC model is flexible because it enables

[4] Eurostoxx gained 4.3% on the day of the speech (8.1% up to the end of July 2012); other important stock indices performed in a similar manner: IBEX 6.1% (13.1%), S&PMIB 5.6% (12.4%), CAC40 4.1% (7.1%), and DAX 2.8% (6.0%).

[5] We also applied Bai-Perron test to detect structural breaks in conditional variances of the examined exchange rates returns. The test shows the significance of structural break in 2008 for all examined exchange rates, which is consistent with the beginning of the GFC mentioned in the paper. Regarding the EU debt crisis, the test suggests different break points for individual new EU exchange rates. To keep the research consistent, we prefer to use the dates based on the well-established economic events described in the text.

[6] The number of parameters to be estimated in the correlation process is independent of the number of series to be correlated. Thus, potentially very large correlation matrices can be estimated. Of course, this comes at the cost of flexibility, as it assumes that all correlations are influenced by the same coefficients.

the estimation of time-varying volatilities, covariances and correlations of various assets over time.[7]

The DCC model is estimated in two stages. In the first stage, univariate GARCH models are estimated for each residual series. In the second stage, residuals transformed by their standard deviation from the first stage are used to construct a conditional correlation matrix.

The multivariate DCC model is specified as follows:

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

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

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

where r_t = $(r_{it}, \ldots, r_{Nt})$' is the (N × 1) vector of exchange rate returns defined in Section 3.1; N=4, as we are examining four exchange rates (CZK/EUR, PLN/EUR, HUD/EUR, USD/EUR); $\mu_t(\theta) = (\mu_{it}, \ldots, \mu_{Nt})$' is the conditional 4 × 1 mean vector of r_t; H_t is the conditional covariance matrix; and $D_t = diag\ (h_{iit}^{\frac{1}{2}}, \ldots, h_{NNt}^{\frac{1}{2}})'$ is a diagonal matrix of square root conditional variances, where h_{iit} can be defined as any univariate GARCH model. R_t is the t*($N(N$-1)/2) matrix containing the time-varying conditional correlation structure, which is defined as follows:

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

In (4), $Q_t = (q_{ij,t})$ is the (N × N) symmetric positive definite matrix given by

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

where $u_t = (u_{1t}, u_{2t}, \ldots, u_{Nt})$' is the N * 1 vector of standardized residuals; $\bar{Q}$ is N * N of the unconditional variance of u_t; and α and β are non-negative scalar parameters satisfying condition $\alpha + \beta < 1$. The DCC model is estimated using a log likelihood function under a heavy-tailed multivariate generalized error distribution (GED).[8]

Based on the characteristics of the DCC model, we formulate Hypothesis 1:

Hypothesis #1: The dynamic conditional correlations between new EU currencies and the U.S. dollar do not change pattern and magnitude across four examined periods.

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[7] Intentionally, we do not use an asymmetric DCC model. Baruník et al. (2017) show that different types of events are characterized by different types of volatility spillover on forex markets. For example, the GFC period is characterized by positive volatility spillovers but during the EU debt crisis negative spillovers dominate the forex market. Since we examine separately periods related to the key financial contagions (the GFC and the EU debt crisis), we do not expect asymmetries to occur in individually examined periods.

[8] A multivariate Student's t error distribution was also employed, but it did not improve our results.

3.3. Hedge ratios and portfolio weights

We use time-varying conditional correlations from the second stage of the DCC model estimation (reported in Table 1) to calculate the optimal diversification of the international currency portfolio. Kroner and Sultan (1993) employ conditional variance and covariance to calculate hedge ratios. Kroner and Ng (1998) then use conditional variance and covariance to design optimal portfolio weights. The hedge ratio is calculated as

$$\beta_{ij,t} = h_{ij,t}/h_{jj,t} \ , \tag{6}$$

where $h_{ij,t}$ is the conditional covariance between the exchange rates of currencies i and j and $h_{jj,t}$ is the conditional variance of currency j at time t. This formula implies that a long-term position in one currency (e.g., i) can be hedged by a short-term position in another currency (e.g., j).

In a portfolio of two currencies optimal portfolio weights between currencies i and j at time t are calculated based on the following formula:

$$w_{ij,t} = \frac{h_{jj,t}-h_{ij,t}}{h_{ii,t}-2h_{ij,t}+h_{jj,t}} \ . \tag{7}$$

In (7), $w_{ij,t}$ is the weight of currency i, and (1 - $w_{ij,t}$) is the weight of currency j. Weights implying the portfolio composition follow the conditions shown below:

$$w_{ij,t} = \begin{cases} 0, & if\ w_{ij,t} < 0 \\ w_{ij,t}, & if\ 0 \leq w_{ij,t} \leq 1 \\ 1, & if\ w_{ij,t} > 1 \end{cases} \ . \tag{8}$$

With respect to the above definitions, we formulate a hedge ratio hypothesis:

Hypothesis #2: Hedge ratios are not stable over all four periods examined.

3.4. Diebold Yilmaz spillover index

To study volatility spillovers between the four examined exchange rates, the Diebold and Yilmaz (2012) spillover index based on the generalized vector autoregressive (VAR) variance decomposition is used. We first employ the following p-order, N-variable VAR model:

$$y_t = \sum_{i=1}^{p} \Theta_i \, y_{t-1} + \varphi_t \tag{9}$$

where φ is a vector of independently and identically distributed errors, $y_t = (y_{1t}, y_{2t}, y_{3t}, y_{4t})$ is a vector of four examined endogenous variables, and Θ is 4 x 4 parameter matrix.

The key to the dynamics of the system is the moving-average representation of model (9), which is given by

$$y_t = \sum_{i=0}^{\infty} A_i \, \varphi_{t-1} \tag{10}$$

where 4 × 4 coefficient matrices A_i are estimated from the recursion
$A_i = \Theta_1 A_{i-1} + \Theta_2 A_{i-2} + \ldots + \Theta_p A_{i-p}$, with A_0 being the 4 × 4 identity matrix and $A_i = 0$ for $i < 0$.

Diebold and Yilmaz (2012) use the generalized VAR framework developed by Koop et al. (1996) and Pesaran and Shin (1998), in which variance decompositions are invariant in terms of the variable ordering. In this case, the H-step-ahead forecast error variance decomposition is defined as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' \, A_h \Sigma \, e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \, \Sigma \, A_h' e_j\right)}\,, \tag{11}$$

where Σ is the variance matrix for the error vector φ, σ_{ii} is the standard deviation of the error term for the *i*th equation, and e_i is the selection vector, with a value of one for the *i*th element and zero otherwise. In the generalized VAR framework, shocks to each variable are not orthogonalized; therefore, the sum of each row of the variance decomposition matrix is not unity $\left(\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1\right)$. In this case, each element of the decomposition matrix is normalized by dividing it by the row sum:

$$\widetilde{\theta_{ij}^{g}}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)}\,, \tag{12}$$

where by construction, $\sum_{j=1}^{N} \widetilde{\theta_{ij}^{g}}(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\theta_{ij}^{g}}(H) = N$.

Using normalized elements of the decomposition matrix of equation (12), we construct the total volatility spillover index:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\theta_{ij}^{g}}(H)}{\sum_{i,j=1}^{N} \theta_{ij}^{g}(H)} * 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\theta_{ij}^{g}}(H)}{N} * 100. \tag{13}$$

This index captures cross-country spillover values by measuring the contributions of volatility spillovers across all countries to the total forecast error variance.

Based on the specification of the total volatility spillover index, we formulate the following hypothesis:

Hypothesis #3: The value of the total volatility spillover index is not stable during the examined time period.

To examine spillover effects from and to a specific currency, we use directional volatility spillovers. Specifically, the directional volatility spillovers received by currency *i* from all other currencies *j* are defined as follows:

$$S^{q}_{i\leftarrow j}(H) = \frac{\sum_{\substack{j=1 \\ i\neq j}}^{N} \widetilde{\theta^{g}_{ij}}(H)}{\sum_{j=1}^{N} \theta^{g}_{ij}(H)} * 100. \tag{14}$$

In a similar fashion, directional volatility spillovers are transmitted by currency *i* to all other currencies *j*.

The net directional volatility spillover provides information about whether a currency is a receiver or transmitter of volatility in net terms, and it is given as follows:

$$S^{g}_{i}(H) = S^{g}_{i\rightarrow j}(H) - S^{g}_{i\leftarrow j}(H). \tag{15}$$

Finally, we formulate a hypothesis about the dominant currency in the volatility transmission mechanism:

Hypothesis #4: None of the examined new EU exchange rates are dominant currencies in terms of volatility transmission mechanisms.

4. Empirical results

4.1 Initial assessment

Dynamics of the studied exchange rates are presented in Figure 1. During the examined time period running from 1999 to 2016, the Czech koruna appreciated and the Hungarian forint depreciated by 29 percent and 19 percent, respectively, against the euro. The Polish zloty oscillated around a value of 4.3. Furthermore, some key patterns were found for USD/EUR. The dollar appreciated against the euro from 1999 to 2002 and reached a minimum value of 0.85. The euro then appreciated against the U.S. dollar until the beginning of the GFC in the fall of 2008, when USD/EUR reached a maximum value of 1.58. After the global financial crises, the euro lost its value.

An analysis of percentage returns shows that all the examined forex markets exhibit the largest volatility in 2008, when the GFC began. The sizable spike in the

CZK/EUR daily returns observed in 2013 is associated with the establishment of currency interventions by the Czech National Bank.[9]

Descriptive statistics of the examined exchange rates are presented in the Appendix (Table A1). The average daily returns are very similar across all four examined exchange rates and close to zero. According to the results of the ADF GLS test, daily exchange rate returns are stationary. For the entire time period examined, the highest standard deviation and the highest volatility are visible in the HUF/EUR and USD/EUR exchange rates. When examining each period separately, the largest standard deviation in Table A1 is associated with the Polish zloty (PLN) during the global financial crisis. The Czech currency exhibits the lowest standard deviation in each analyzed period. In other words, the Czech koruna (CZK) is the least volatile currency of the three new EU currencies examined. In addition, the standard deviations of the four exchange rates decrease after the EU debt crisis; the finding demonstrates lower levels of contagion and financial distress. Further, the skewness and excess kurtosis values of all exchange rates examined in Table A1 indicate that the time series are not normally distributed; this is also confirmed by the *p*-value of the Jarque-Bera test, which indicates that the null hypothesis may be rejected at the 1% level significance. Exchange rates are mostly skewed to the right, implying the existence of several small and few large returns. The HUF/EUR and the USD/EUR returns exhibit the largest kurtosis and skewness values. The CZK/EUR skewness and kurtosis values temporarily increased after the Czech central bank launched currency interventions in 2013.

Finally, Table A1 presents the Ljung-Box test Q and Q^2 statistical results. The results reveal the presence of a serial correlation in squared returns for almost all the time series examined, implying the presence of non-linear dependencies. Moreover, according to Engle's ARCH-LM statistics, an ARCH effect is present in the data at the 1% significance level. Overall, the exchange rate returns exhibit patterns of volatility persistence and clustering, in addition to non-linear dependency. These results support application of GARCH-type models.[10]

[9] The CNB practiced an "exchange rate commitment" (constraining exchange rate regimes) from November 7, 2013 to April 6, 2017. The CNB prevented the koruna from undergoing excessive appreciation to below CZK 27/EUR by intervening in the forex market. On the weaker side of the CZK 27/EUR level, the CNB allowed the koruna exchange rate to float.

[10] Both the HUF/EUR and USD/EUR values for during the EU debt crisis and the CZK/EUR and USD/EUR values for after the EU debt crisis reject the null hypothesis of an absence of ARCH effects. This can be attributed to the fewer observations included in these samples. The absence of ARCH effects found in the CZK/EUR can be explained by central bank currency interventions and by the oscillation of the CZK/EUR at around 27.00 from November 7, 2013 to the end of the examined time series.

4.2. DCC model-exchange rate co-movements

Table 1 presents the results of the time-varying exchange rate co-movements based on the DCC-GARCH model described in Section 3.2. To remove any serial correlation in returns, the AR(1)-DCC-GARCH model is employed when a serial correlation is found in residuals of the GARCH model. We apply GED distributions to the residuals.

As a common pattern, the new EU exchange rates behave homogenously in individually examined time periods and exhibit common behaviors in terms of co-movements with USD/EUR. The magnitude of correlations between new EU exchange rates and the U.S. dollar is highest prior to the GFC and lowest during the EU debt crisis. Specifically, Figures 2 A-C show correlations ranging from 0.8 (forint – U.S. dollar) prior to the GFC to negative 0.5 during the EU debt crisis (forint – U.S. dollar and zloty – U.S. dollar).[11] Correlations between new EU currencies and USD/EUR demonstrate weaker conditional correlations than the currencies of developed countries. For example, Antonakakis (2012) shows that the conditional correlations between the exchange rates of major currencies are entirely positive and range from 0.32 (JPY/GBP) to 0.87 (CHF/EUR).

We assess whether the difference in the time-varying magnitude of two conditional correlations (ρ), reported in Table 1, is statistically significant. In the same way as Basu (2002) and Chiang et al. (2007) we apply the Z-transformation introduced by Fisher (1915). The null hypothesis of Z-transformation states that conditional correlations of two samples are equal. We compare conditional correlations in pairs of neighboring samples representing neighboring time periods. Based on the results in Table 2 we are able to reject the null hypothesis for all period-pairs and all new EU currencies.[12] The results provide evidence that dynamic conditional correlations are not constant and their magnitudes differ in between the four examined time periods. The above results allow us to reject Hypothesis 1.

[11] We considered the downward bias estimation problem related to the DCC model. Hafner and Reznikova (2012) suggest that the bias is considerable for a small number of observations and vanishes when the number of observations increases. Therefore we performed robustness check by calculating the DCC model for the whole period of 17 years (1999-2016). In this model, the individual periods such as the GFC and the EU debt crisis are reflected by the dummy variables.

[12] In the Fisher Z-Transformation the correlation coefficients are converted to normally distributed Z variables (Z_0, Z_1) by this formula: $Z_0 = \frac{1}{2}\ln[\frac{1+\rho_0}{1-\rho_0}]$ and $Z_1 = \frac{1}{2}\ln[\frac{1+\rho_1}{1-\rho_1}]$, where ρ_0 and ρ_1 are correlation coefficients in individually examined time periods. Consequently, the values for the Fisher Z-Test are calculated by formula: $T = \frac{Z_0 - Z_1}{\sqrt{\frac{1}{N_0-3}+\frac{1}{N_1-3}}}$, where N_0 and N_1 denote the number of observations in individually examined time periods. Positive z-value indicates that ρ_0 is larger than ρ_1; negative z-value demonstrates that ρ_0 is smaller than ρ_1. The critical value for the Fisher Z-test at the 1, 5 and 10% level statistical significance is 1.28, 1.65 and 1.96.

4.2.1. Prior to the global financial crisis (GFC)

In Figures 2 A-C, we present time-varying correlations between USD/EUR and the new EU exchange rates. Our figures reveal different patterns of co-movements in the forex market. Strongly increasing correlations between USD/EUR and three new EU currencies from 1999 to 2002 correspond to the time during which the euro was used as an electronic/accounting currency in 11 of the 15 EU member states. Conditional correlations between the forint and the U.S. dollar and between the zloty and the U.S. dollar reach values of nearly 0.8 during this time. In 2002, euro notes and coins became legal tender in the 12 Eurozone countries (Greece was the 12th member). From this point on, dynamic conditional correlations of the USD/EUR and the new EU currencies decrease. Koruna – U.S. dollar correlations reach the lowest value of negative 0.2, zloty – U.S. dollar correlations decrease to negative 0.4, and forint – U.S. dollar correlations reach negative 0.6 just prior to the GFC. The estimated parameters of the DCC model (α and β) in Table 1 are statistically significant at the 1% level, indicating that the model is well specified and confirming that the second moments of exchange returns are indeed time varying (α). Moreover, high values found for parameter β and especially for the koruna – U.S. dollar relation suggest the presence of a strong correlation structure. The zloty – U.S. dollar relation exhibits the highest conditional correlation (0.26). In contrast, the koruna – U.S. dollar relation reaches a slightly negative correlation, with a value of negative 0.02, for this point in time.

4.2.2 The global financial crisis (GFC)

Dynamic conditional correlations found between the new EU exchange rates and USD/EUR continue to decrease during the GFC. Nevertheless, this decline is gentle, and the correlations usually oscillate at approximately negative 0.2 (koruna – U.S. dollar), negative 0.3 (forint – U.S. dollar) and negative 0.4 (zloty – U.S. dollar), as indicated in Table 1 and Figures 2A (koruna), 2B (zloty), and 2C (forint). The absence of a time-varying correlation structure for koruna – U.S. dollar returns is suggested by the insignificant parameter α in the DCC equation. Further, lower levels of parameter β in the DCC equation in Table 1 imply lower levels of correlation memory.

4.2.3. The EU debt crisis

The dynamic correlations exhibit patterns of behavior for the EU debt crisis that are similar to those observed for the GFC period. Again, the correlations decrease slightly and reach the lowest values of those observed in the four periods examined. The conditional correlations decrease to negative 0.3 (koruna – U.S. dollar) and negative 0.5 (zloty – U.S. dollar; forint – U.S. dollar), as indicated in Table 1 and Figures 2A (koruna), 2B (zloty) and 2C (forint). The dynamic conditional correlations record lower values during the EU debt crisis than during the GFC. The absence or low statistical significance of parameter α denotes an absence of time-varying correlation structures. The fact that this parameter reaches lower values during the EU debt crisis comparing to the GFC period, indicate more stable and less volatile conditional correlations during the EU debt crisis. The statistical insignificance of coefficient β found for the forint - U.S. dollar relation implies an absence of correlation memory. The results of Kasch and Caporin (2013), who apply the extended DCC model, indicate that turbulent periods are associated with an increase in correlations among developed stock markets. A similar argument is put forth by Ang and Chen (2002). However, for cross-correlations between the new EU currencies, and for the Hungarian and Czech currency markets in particular, this pattern is far less pronounced. Negative values of correlations in this paper demonstrate an absence of positive co-movements in new EU forex markets during both recent crises. These findings contradict the evidence in the literature.

4.2.4. After the EU debt crisis

Following the EU debt crisis, the conditional correlations between new EU currencies and USD/EUR increase to 0.2 at the beginning of 2015, as we indicate in Table 1 and Figures 2A (koruna), 2B (zloty), and 2C (forint). The reversion of the correlations' values approaching pre-crisis levels may be related to the improving conditions in the financial market following the end of the GFC and EU debt crises. At the beginning of 2015, ECB announced the implementation of a quantitative easing (QE) program by buying each month bonds at a value of 80 bn. euros from commercial banks. The correlations of all new EU exchange rates begun instantly falling towards the negative territory close to levels observed during the EU debt crisis. Later, during the second half of 2016, the correlations slowly return to pre-crisis levels.

The Czech National Bank (CNB) launched forex interventions on November 7, 2013 and used them until April 6, 2017. The central bank prevented the koruna from excessive appreciation below CZK 27/EUR by intervening in the forex market. On the weaker side of CZK 27/EUR, the CNB allowed the koruna exchange rate to float. We use the dummy variable in the GARCH equation to capture the effect of currency interventions. A dummy variable may not always sufficient reflect extremely low returns on koruna during the period of constraining exchange rate regime. For this purpose, we also report time-varying conditional correlations for the koruna - U.S. dollar relation separately during the period not affected by currency interventions from January 1, 1999 until November 6, 2013; see Appendix Figure A2 for details.

4.3. Hedge ratios and portfolio weights

The comprehensive portfolio weights and hedge ratios are presented in Table 3. Overall, the portfolio weights are found to be stable across all examined periods and reach the value close to 50 percent. For example, the average weight for the CZK/HUF prior to the GFC is 0.5349, indicating that on average, in a 1-euro portfolio, 0.5349 euros should be invested in the CZK, and 0.4651 euros should be invested in HUF. After the EU debt crisis, the portfolio weights for the CZK decrease to 0.5010. Particularly, on average in 1-euro portfolio, 0.5010 euros should be invested in the CZK, and 0.4990 euros should be invested in the HUF.

Excessive volatility in the financial markets renders the hedge more expensive. For example, a 1-euro long position in the CZK should be hedged by a 0.32 PLN short position prior to the EU debt crisis. During the GFC, we need to open short position in the PLN of 0.56 to hedge 1-euro long position in the CZK. This means that during the GFC we need 75 percent more PLN to hedge our 1-euro long position in the CZK. Overall, the hedging costs increase by 75 percent due to market distress, uncertainty and increased volatility. The unfavorable conditions in the examined forex market during the GFC are also represented by the high level of standard deviation indicated in Appendix Table A1.

During the EU debt crisis, the average costs of hedging slowly decrease. 1-euro long position in the CZK can be hedged with 0.43 short position in the PLN. After the EU debt crisis, we need to open only the short position in the PLN of 0.24 to hedge 1-euro long position in the CZK. We posit that the non-standard monetary policy measures taken by the ECB in response to the crisis eased market distress. Overall, we cannot reject Hypothesis 2.

Further, the results presented Table 3 indicate that the cheapest hedge is a long position in the Czech koruna and a short position in the Hungarian forint in all periods examined except from the GFC. On the other hand, the most expensive hedge is a long position in the Polish zloty and a short position in the Hungarian forint. Finally, none of the hedge ratios are in excess of unity in all periods examined. These results resonate with those of Antonakakis (2012), who show that after establishment of the euro, the developed currencies' hedge ratios stay below unity.

4.4. The Diebold Yilmaz spillover index

The results of volatility spillovers based on the Diebold and Yilmaz generalized spillover index are presented in Table 4 and Figures 3-6. Here, we present the directions and degrees of volatility spillovers within and across all four exchange rates.[13]

Table 4 presents a numerical aggregation of the dynamic patterns observed. In Figure 3, we present the results of the estimated time-varying total volatility spillover index based on 200-day rolling samples. We observe considerable levels of variability in the index immediately following the introduction of the euro (1999-2000). The index value peaks at above 20 percent in 2006 and again at the start of 2008 and in 2009. The two peaks, in 2008 and 2009, correspond to the GFC period. Finally, after the EU debt crisis, the spillover index remains at lower than pre-crisis levels.

The diagonal values (i = j) of the total spillover index presented in Table 4 are higher than off-diagonal values (i ≠ j). The results indicate that own-currency volatility explains a substantial share of volatility spillovers. These results are in line with those of Bubák et al. (2011), who find that during the pre-2008 period, the volatilities of both the EUR/CZK and the EUR/PLN exchange rates are affected chiefly by their own histories in terms of both the short-term and long-term volatility patterns. When examining each time period separately, the largest off-diagonal volatility spillovers are (i) bidirectional spillovers between zloty-koruna, forint-koruna and forint-zloty during the GFC and (ii) bidirectional spillovers between the

[13] The daily variance ($\tilde{\sigma}_{it}^2$) is estimated for currency i and day t using the formula suggested by Diebold and Yilmaz (2012). $\tilde{\sigma}_{it}^2 = 0.361\left[ln(P_{i,t+1}^{close}) - \ln(P_{i,t}^{close})\right]^2$, where $P_{i,t+1}^{close}$ is the closing price of currency i on day $t + 1$ and $P_{i,t}^{close}$ is the closing price of currency i at time t.

zloty-forint during the EU debt crisis. These findings are consistent with those of Antonakakis (2012), who find that market volatility exhibits bidirectional volatility spillovers rather than unidirectional volatility spillovers between the euro and other developed market currencies.

The total volatility spillover index reaches its highest value of 21.6 percent during the GFC (see Table 4). Further, the GFC is characterized by higher levels of volatility, as the values of the own- currency (diagonal) volatility decrease and cross-currency (off-diagonal) volatility increases.[14] These results imply that during the GFC, higher levels of volatility spill over to individual currencies from their forex counterparts. The highest off-diagonal spillover values can be observed between the forint and the zloty and between the forint and the koruna. As the GFC resolved, off-diagonal volatility decreases but remains relatively high during the EU debt crisis, with a total volatility spillover index reaching the level of 8.96 percent. The largest cross-currency spillovers occurred from the zloty to the forint. Both the GFC and the EU debt crisis stand in contrast to calmest period prior to the GFC, when, on average, 4.13 percent of the volatility forecast error variance for all four currencies can be attributed to volatility spillovers. Consequently, we cannot reject null Hypothesis 3.

In terms of individual effects, the Hungarian forint is the dominant currency in terms of volatility transmission for each individually examined time period according to the "Contributions to others" row of Table 4. Contrary, the Czech koruna transmits the lowest proportion of volatility prior to the GFC and during the EU debt crisis. From the other perspective, the Polish zloty assumes a leading role as volatility spillovers receiver prior to the GFC and during the EU debt crisis. Such spillovers are mainly received by the Czech koruna during the GFC...[15] These findings allow us to reject Hypothesis 4.

Further, the total volatility spillover index (in aggregated or dynamic form) does not provide on information about the direction of the spillovers. For this reason, we construct Figures 4 and 5 based on formula (14) and using 200-day rolling samples. Figure 4 presents directional volatility spillovers FROM each of the four currencies to others. Figure 5 presents directional volatility spillovers from other

[14] To estimate the total volatility spillover index, we apply the VAR(4) and VAR(5) models according to the Akaike Information Criterion (AIC). Variance decompositions are based on 10-step-ahead forecasts and 200-day rolling windows for all the time periods examined.

[15] These findings may not correspond with net spillover values (last row) in Table 4 due to the presence of bidirectional volatility spillovers.

currencies TO each individual currency for all three periods examined.[16] These figures depict the development of volatility patterns over the study period. According to Figures 4 and 5, the Hungarian forint confirms its leading role in volatility transmission, reaching very high values in all four examined periods. Further, the koruna and the zloty receive the highest volatility during the GFC, whereas the euro faces the highest volatility from outside during the EU debt crisis.

Finally, Figure 6 shows net volatility spillovers from/to each of the four examined exchange rates computed using equation (15) based on 200-day rolling windows. USD/EUR is a net receiver of volatility from 2004-2006 and during the GFC. However, USD/EUR becomes source of volatility transmissions to the new EU currencies with the start of the EU debt crisis. The Hungarian forint is the most vulnerable currency during the EU debt crisis, as it is a net volatility receiver during the period of 2010-2012. Finally, the Czech koruna is mostly a net volatility receiver following the EU debt crisis, which may be explained by Czech National Bank having adopted a constraining exchange rate regime that involved use of the currency interventions.

5. Conclusion

We analyze time-varying exchange rate co-movements and volatility spillovers in the new EU forex market over 1999-2016. Specifically, we examine conditional correlations and volatility spillovers between the Czech, Hungarian, and Polish currencies and the US dollar; all currencies are expressed with respect to the euro. We employ the DCC model and Diebold-Yilmaz spillover index as the key tools of our analysis. Our results document the evolution of currency interdependencies and volatility spillovers during calm as well as distress periods (the GFC and EU debt crisis).

We show that conditional correlations change over time and may be evaluated from the perspective of major economic events. During the first three years of the euro's existence (1999-2001), all three new EU currencies exhibit their strongest correlations with the U.S. dollar. Since 2002, the correlations have decreased towards negative values. The conditional correlations reach the lowest values during the GFC and the EU debt crisis. After the EU debt crisis, the correlations strengthen and return back to pre-crisis levels. These outcomes go against general understanding that

[16] The figures correspond to the "Contributions to others" row and the "Contributions from others" column in Table 4.

correlations between financial assets increase during turbulent periods. On contrary, low correlations on the new EU forex markets during periods of distress offer valuable diversification opportunities.

These potential portfolio benefits come at some costs, though. We use the data from the DCC model in a simulated portfolio management exercise. We use time-varying magnitude of the correlations from the second stage of DCC model estimation to calculate portfolio weights and hedge ratios. We demonstrate that hedging during the GFC is 75 percent more expensive than before the GFC. Generally, on the new EU forex market, the hedging is most costly during the GFC and the cheapest hedging is observed in the period after the EU debt crisis.

In terms of volatility spillovers, the highest levels of cross-currency volatility are found during the GFC. Further, we find that own-currency volatility spillovers explain a substantial share of the total volatility. Volatility spillovers between individual currencies can be characterized as bidirectional volatility spillovers. In this respect, the Hungarian forint is the dominant currency of the volatility transmission mechanism in that it transmits most spillovers from other currencies in each time period examined.

The results we present carry important implications for both forex market regulators as well as its actors in the EU. We document significant differences in the extent of currency co-movements during various periods related to market distress. The extent of distress is further related to real economic and financial events. Moreover, low correlations between new EU currencies during periods of financial distress represent less than obvious results and imply favorable diversification benefits for the investors investing in the new EU currencies. However, the diversification potential comes with costly hedging. The costs of hedging during different periods of distress are not uniform and we show that the most costly enterprise is to offset potential losses during the GFC and the EU debt crisis. Volatility spillovers raged the new EU forex markets most during both crises as well.

References

Aloui, R., Ben Aïssa, M.S., Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure? Journal of Banking and Finance, 35, 130-141.

Adrian, T., Brunnermeier, M. (2016). CoVaR. American Economic Review, 106(7), 1705–1741.

Andrieş, A.M., Ihnatov, I., Tiwari, A.K. (2016). Comovement of Exchange Rates: A Wavelet Analysis. Emerging Markets Finance and Trade, 52(3), 574-588.

Ang, A., Bekaert, G. (2002). International asset allocation with regime shifts. Review of Financial Studies, 15(4), 1137-1187.

Ang, A., J. Chen. (2002). Asymmetric Correlations of Equity Portfolios. Journal of Financial Economics, 63(3), 443-494.

Antonakakis, N. (2012). Exchange return co-movements and volatility spillovers before and after the introduction of euro. Journal of International Financial Markets, Institutions & Money, 22(5), 1091–1109.

Antonakakis, N., Kizys, R. (2015). Dynamic spillovers between commodity and currency markets. International Review of Financial Analysis, 41, 303-319.

Bank for International Settlements (BIS). (2016). Triennial Central Bank Survey Foreign exchange turnover in April 2016. Available online (www.bis.org/publ/rpfx16.htm).

Baruník, J., Kočenda, E., Vácha, L. (2017). Asymmetric volatility connectedness on the forex market. Journal of International Money and Finance, 77, 39-56.

Basu, R. (2002). Financial contagion and investor 'learning': an empirical investigation. IMF working paper No. 02/218.

Baum, C., Caglayan, M., Barkoulas, J. (2001). Exchange rate uncertainty and firm profitability. Journal of Macroeconomics, 23 (4), 565–576.

Bekiros, S., Marcellino, M. (2013). The multiscale causal dynamics of foreign exchange markets. Journal of International Money and Finance, 33, 282–305.

Belke, A., Gros, D. (2002). Designing EU–US Atlantic monetary relations: exchange rate variability and labour markets. World Economy, 25(6), 789–813.

Black, F. (1976). Studies of Stock Price Volatility Changes. Proceedings of the 1976 Meetings of the American Statistical Association, Business and Economic Statistics, 177-181.

Boero, G., Silvapulle, P., Tursunalieva, A. (2011). Modelling the bivariate dependence structure of exchange rates before and after the introduction of the euro: a semi-parametric approach. International Journal of Finance & Economics, 16(4), 357–374.

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. Journal of Econometrics 31, 307-327.

Bollerslev, T. (1990). Modelling the coherence in short-run nominal exchange rates: a multivariate generalized ARCH model. Review of Economics and Statistics, 72(3), 498–505.

Bubák, V., Kočenda, E., Žikeš, F. (2011). Volatility transmission in emerging European foreign exchange markets. Journal of Banking & Finance, 35(11), 2829-2841.

Chiang, T.C., Jeon, B.N., Li, H. (2007). Dynamic correlation analysis of financial contagion: Evidence from Asian markets. Journal of International Money and Finance, 26(7), 1206-1228.

DeMiguel, V., L. Garlappi, R. Uppal. (2009): Optimal versus naïve diversification: How inefficient is the 1/N portfolio strategy? Review of Financial Studies, 22(5), 1915-1953.
Diebold, F. X., Yilmaz, K. (2009). Measuring financial asset return and volatility spillovers, with application to global equity markets. The Economic Journal, 119(534), 158-171.
Diebold, F.X., Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. International Journal of Forecasting, 28 (1), 57–66.
Diebold, F.X., Yilmaz, K. (2015). Financial and Macroeconomic Connectedness: A Network Approach to Measurement and Monitoring. Oxford University Press, USA
Engle, R. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroscedasticity models. Journal of Business & Economic Statistics, 20(3), 339-350.
Fisher, R.A. (1915). Frequency distribution of the values of the correlation coefficient in samples of an indefinitely large population. Biometrika, 10(4), 507–521.
Fiordelisi, F., Ricci, O. (2016). "Whatever it takes": An Empirical Assessment of the Value of Policy Actions in Banking. Review of Finance, 20(6), 2321–2347.
Frankel, J., Saravelos, G. (2012). Can leading indicators assess country vulnerability? Evidence from the 2008–09 global financial crisis. Journal of International Economics, 87(2), 216-231
Fujiwara, I., K. Takahashi. (2012). Asian financial linkage: Macro-finance dissonance. Pacific Economic Review, 17 (1), 136–159.
Greenwood-Nimmo, M.J., Nguyen, V.H., Rafferty, B. (2016). Risk and return spillovers among the G10 currencies. Journal of Financial Markets, 31(C), 43–62.
Groh, A. P., Von Liechtenstein, H. (2009). How attractive is central Eastern Europe for risk capital investors? Journal of International Money and Finance, 28(4), 625-647.
Hafner, C.M., Reznikova, O. (2012). On the estimation of dynamic conditional correlation models. Computational Statistics and Data Analysis, 56(11), 3533–45.
Hanousek, J., Kočenda, E. (2011). Foreign News and Spillovers in Emerging European Stock Markets. Review of International Economics, 19(1), 170-188.
Hanousek, J., Kočenda, E., Novotny, J. (2014). Price jumps on European stock markets. Borsa Istanbul Review, 14(1), 10-22.
Inagaki, K. (2007). Testing For Volatility Spill over between the British Pound and the Europe. Research in International Business and Finance, 21(2), 161–174.
Jotikasthira, Ch., Lundblad, Ch., Ramadorai, T. (2012). Asset Fire Sales and Purchases and the International Transmission of Funding Shocks. Journal of Finance, 67(6), 2015-2050.
Kanas, A. (2001). Volatility spillovers between stock returns and exchange rate changes: International evidence. Journal of Business Finance and Accounting, 27 (3), 447-465.
Kasch, M., Caporin, M. (2013). Volatility Threshold Dynamic Conditional Correlations: An International Analysis. Journal of Financial Econometrics, 11(4), 706–742.

Kitamura, Y. (2010). Testing for intraday interdependence and volatility spillover among the Euro, the pound and the Swiss franc markets. Research in International Business and Finance, 24(2), 158-171.
Koop, G., Pesaran, M.H., Potter, S.M. (1996). Impulse response analysis in nonlinear multivariate models. Journal of Econometrics, 74(1), 119–147.
Kroner, K.F., Ng, V.K. (1998). Modeling asymmetric movements of asset prices. Review of Financial Studies, 11(04), 817–844.
Kroner, K.F., Sultan, J. (1993). Time-varying distributions and dynamic hedging with foreign currency futures. Journal of Financial and Quantitative Analysis, 28(4), 535–551.
Kumar, M. (2013). Returns and volatility spillover between stock prices and exchange rates: Empirical evidence from IBSA countries. International Journal of Emerging Markets, 8(2), 108-128.
Longin, F., B. Solnik. (2001). Extreme correlations in international Equity Markets. Journal of Finance, 56(2), 649-676.
McMillan, D. G., Speight, A. E. (2010). Return and Volatility Spill over in Three Euro Exchange Rates. Journal of Economics and Business, 62(2), 79-93.
Nikkinen, J., Sahlström, P., Vähämaa, S. (2006). Implied Volatility Linkages among Major European Currencies. Journal of International Financial Markets, Institutions and Money, 16(2), 87–103.
Pesaran, H.H., Shin, Y. (1998). Generalized impulse response analysis in linear multivariate models. Economics Letters, 58(1), 17–29.
Pramor, M., Tamirisa, N.T. (2006). Common Volatility Trends in the Central and Eastern European Currencies and the Euro. IMF Working Paper, WP/06/206.
Rose, A. (2000). One money, one market: the effect of common currencies on trade. Economic Policy, 30 (April), 9–45.
Singh, P., Kumar, B., and Pandey, A. (2010). Price and volatility spillover across North American, European and Asian stock markets. International Review of Financial Analysis, 19(1), 55-64.
Stracca, L. (2015). Our currency, your problem? The global effects of the euro debt crisis. European Economic Review, 74, 1-13.
Taylor, S.J. (1986). Forecasting the Volatility of Currency Exchange Rates. International Journal of Forecasting 3, 159-170.
Tse, Y.K., Tsiu, A.K.C. (2002). A multivariate generalized autoregressive conditional heteroscedasticity model with time-varying correlations. Journal of Business & Economic Statistics, 20(3), 351-362.
Wu, G. (2001). The Determinants of Asymmetric Volatility. Review of Financial Studies, 14(3), 837-59.

Table 1

Estimation results of the DCC model.

	Before the GFC (1.1.1999-30.4.2010)			**The GFC (15.9.2008 - 30.4.2010)**			**EU debt crisis (3.5.2010-25.7.2012)**			**After EU debt crisis (26.7.2012-30.12.2016)**		
1st step univariate GARCH model and diagnostic tests												
Mean Eq.	**CZK/EUR**	**PLN/EUR**	**HUF/EUR**	**CZK/EUR**	**PLN/EUR**	**HUF/EUR**	**CZK/EUR**	**PLN/EUR**	**HUF/EUR**	**CZK/EUR**	**PLN/EUR**	**HUF/EUR**
Constant	-0.0002**	-0.0003**	0.0000	-0.0001	-0.0001	-0.0002	0.0000	-0.0001	-0.0000	0.0000***	-0.0000	-0.0000
	(0.0022)	(0.0003)	(0.6092)	(0.6167)	(0.7167)	(0.5626)	(0.8984)	(0.5321)	(0.7445)	(0.0000)	(0.6579)	(0.9920)
Variance Eg.												
Constant	0.0000**	0.0000**	0.0000**	0.0000	0.0000	0.0000	0.0000	0.0000*	0.0000*	0.0000	0.0000**	0.0000
	(0.0002)	(0.0002)	(0.0000)	(0.4352)	(0.3641)	(0.1719)	(0.1556)	(0.0292)	(0.0331)	(0.0776)	(0.0080)	(0.1151)
α	0.0699**	0.0885**	0.0488**	0.0883**	0.0736**	0.1167**	0.0680**	0.0412*	0.0312*	0.1878**	0.1396**	0.0371**
	(0.0000)	(0.0000)	(0.0000)	(0.0013)	(0.0016)	(0.0002)	(0.0071)	(0.0345)	(0.0213)	(0.0000)	(0.0000)	(0.0016)
β	0.9029**	0.8945**	0.9486**	0.9042**	0.9185**	0.8762**	0.9174**	0.9189**	0.9515**	0.8118**	0.8187**	0.9525**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GED parameter	1.2184**	1.4001**	1.5000**	1.5488**	1.5233**	1.4561**	1.3821**	1.4235	1.5344**	1.0108	1.3576**	1.4826**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Q(30)	13.1960	39.1860	16.0630	38.1710	25.6370	19.5450	23.2320	28.4040	26.2310	20.5300	23.3190	23.4110
	(0.9970)	(0.1220)	(0.9820)	(0.1450)	(0.6940)	(0.9280)	(0.8060)	(0.5490)	(0.6630)	(0.8270)	(0.8020)	(0.7980)
$Q^2(30)$	15.1510	29.0830	0.7264	20.7560	22.2590	17.6920	22.9460	36.8240	14.2490	1.5785	18.0820	30.6740
	(0.9890)	(0.5130)	(1.0000)	(0.8950)	(0.8440)	(0.9630)	(0.8170)	(0.1820)	(0.9930)	(1.0000)	(0.9570)	(0.4320)
2nd step DCC model. correlations												
ρ (corr)	-0.0221	0.2631	0.0560	-0.1694	-0.3273	-0.3730	-0.2963	-0.4819	-0.4927	-0.0927	-0.0499	-0.0616
α	0.0076**	0.0287**	0.0413**	0.0307	0.1091**	0.0714*	0.0206*	0.0331*	0.0132	0.0198*	0.0183**	0.0253**
	(0.0010)	(0.0000)	(0.0000)	(0.3861)	(0.0015)	(0.0414)	(0.0172)	(0.0301)	(0.6084)	(0.0184)	(0.0000)	(0.0004)
β	0.9905**	0.9651**	0.9552**	0.7300	0.7110**	0.8087**	0.9657**	0.8962**	0.7864	0.9625**	0.9731**	0.9562**
	(0.0000)	(0.0000)	(0.0000)	(0.0592)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2308)	(0.0000)	(0.0000)	(0.0000)
Log-Lik	25.8242	232.4878	96.39579	6.8990	37.4631	36.4078	31.6512	80.5613	80.3013	12.5475	16.9434	11.2316

Notes: Q(30) and Q2(30) are Ljung-Box portmanteau test statistics for serial correlations of the univariate standardized and squared standardized residuals, respectively; p-values are presented in parentheses. Following Antonakakis (2012) the number of lags was set to 30 to reflect potential one-month seasonality in the data; * denotes 5% significance; ** denotes 1% significance.

The GARCH models for individual time periods were chosen following these criteria: (i) eliminating the ARCH effect from the residuals, (ii) eliminating serial correlations in the residuals, and (iii) considering the best AIC and SIC criterion. Because the standard GARCH (1,1) model fulfilled the criteria, we consider this model sufficient for the calculations of the DCC model. GARCH models with higher lags, asymmetric GARCH-type models (EGARCH, TARCH), and Student's (t) error distribution were also estimated, but they were not able to deliver improved results in terms of the AIC and SIC.

Table 2

Z-transformation (Fisher, 1915).

	Before GFC & GFC	
	Z-test statis	**p-value**
CZK/EUR & USD/EUR	2.8000	0.0079
PLN/EUR & USD/EUR	-11.4518	0.0000
HUF/EUR & USD/EUR	-8.4203	0.0000
	GFC & EU debt crisis	
	Z-test statis	**p-value**
CZK/EUR & USD/EUR	-2.0816	0.0457
PLN/EUR & USD/EUR	-2.8752	0.0064
HUF/EUR & USD/EUR	-2.2877	0.0291
	EU debt crisis & After EU debt crisis	
	Z-test statis	**p-value**
CZK/EUR & USD/EUR	4.1464	0.0001
PLN/EUR & USD/EUR	9.2787	0.0000
HUF/EUR & USD/EUR	9.3261	0.0000

Note: Table reports Z-statistics and p-values for the Z-transformation

Table 3

Hedge ratio and portfolio weight summary statistics.

Before GFC period (1.1.1999 - 12.9.2008)					**GFC period (15.9.2008 - 30.4.2010)**				
Hedge ratio (long/short)					***Hedge ratio (long/short)***				
	Mean	Std. dev.	Min	Max		Mean	Std. dev.	Min	Max
CZK/PLN	0.3151	0.1953	-0.2840	0.8418	CZK/PLN	0.5611	0.0819	0.2703	0.8343
CZK/HUF	0.2325	0.1618	-0.2864	0.6677	CZK/HUF	0.5809	0.0399	0.4565	0.6742
PLN/HUF	0.4370	0.1733	-0.0229	0.8657	PLN/HUF	0.7159	0.0644	0.5288	0.8594
Portfolio weights (currency i/currency j)					***Portfolio weights (currency i/currency j)***				
CZK/PLN	0.5055	0.1524	0.0613	1.0866	CZK/PLN	0.5002	0.0907	0.1681	0.7800
CZK/HUF	0.5349	0.1981	0.1524	0.9843	CZK/HUF	0.4962	0.0529	0.3743	0.6897
PLN/HUF	0.5673	0.1981	0.1292	1.1217	PLN/HUF	0.4915	0.0869	0.2479	0.7426
EU debt crisis (3.5.2010 - 25.7.2012)					**After EU debt crisis (26.7.2012 - 30.12.2016)**				
Hedge ratio (long/short)					***Hedge ratio (long/short)***				
	Mean	Std. dev.	Min	Max		Mean	Std. dev.	Min	Max
CZK/PLN	0.4299	0.1009	0.2254	0.6513	CZK/PLN	0.2442	0.0442	0.0734	0.5561
CZK/HUF	0.4189	0.0531	0.3065	0.5126	CZK/HUF	0.1610	0.0064	0.1403	0.1941
PLN/HUF	0.6355	0.0780	0.3724	0.8731	PLN/HUF	0.5467	0.0925	0.2602	0.7388
Portfolio weights (currency i/currency j)					***Portfolio weights (currency i/currency j)***				
CZK/PLN	0.5002	0.0462	0.3944	0.6527	CZK/PLN	0.5016	0.0337	0.2293	0.6242
CZK/HUF	0.5010	0.0264	0.4475	0.5997	CZK/HUF	0.5010	0.0051	0.4506	0.5133
PLN/HUF	0.4968	0.1066	0.1026	1.0435	PLN/HUF	0.5027	0.0889	0.3140	0.7019

Table 4

Volatility spillovers.

Before GFC	*From j*				
To i	**CZK/EUR**	**PLN/EUR**	**HUF/EUR**	**USD/EUR**	**Contribution from others**
CZK/EUR	96.90	0.96	1.20	0.94	3.1
PLN/EUR	1.01	94.16	2.45	2.39	5.8
HUF/EUR	0.68	2.10	96.30	0.92	3.7
USD/EUR	0.69	1.66	1.61	96.03	3.9
Contribution to others	2.4	4.7	5.3	4.3	**Index:**
Contribution including own	99.3	98.9	101.6	100.3	4.13%
Net Spillover	-0.7	-1.1	1.6	0.4	

GFC period	*From j*				
To i	**CZK/EUR**	**PLN/EUR**	**HUF/EUR**	**USD/EUR**	**Contribution from others**
CZK/EUR	76.28	8.27	10.39	5.06	23.7
PLN/EUR	8.68	77.70	9.33	4.29	22.3
HUF/EUR	8.86	9.79	76.67	4.68	23.3
USD/EUR	6.20	5.00	5.97	82.83	17.2
Contribution to others	23.7	23.1	25.7	14.0	**Index:**
Contribution including own	100.0	100.7	102.4	96.9	21.60%
Net Spillover	0.00	0.8	2.4	-3.2	

EU debt crisis	*From j*				
To i	**CZK/EUR**	**PLN/EUR**	**HUF/EUR**	**USD/EUR**	**Contribution from others**
CZK/EUR	95.81	1.11	1.39	1.69	4.19
PLN/EUR	1.53	86.77	7.94	3.76	13.23
HUF/EUR	1.43	8.82	87.18	2.57	12.82
USD/EUR	2.10	1.34	2.19	94.38	5.63
Contribution to others	5.06	11.27	11.52	8.02	**Index:**
Contribution including own	100.87	98.04	98.70	102.40	8.96%
Net Spillover	0.87	-1.96	-1.30	2.39	

After EU debt crisis	*From j*				
To i	**CZK/EUR**	**PLN/EUR**	**HUF/EUR**	**USD/EUR**	**Contribution from others**
CZK/EUR	94.07	2.05	3.09	0.80	5.94
PLN/EUR	0.93	92.74	4.88	1.44	7.25
HUF/EUR	3.44	4.04	91.62	0.90	8.38
USD/EUR	1.58	1.14	1.42	95.86	4.14
Contribution to others	5.95	7.23	9.39	3.14	**Index:**
Contribution including own	100.02	99.97	101.01	99.00	6.42%
Net Spillover	0.01	-0.02	1.01	-1.00	

Notes: Values reported are variance decompositions for the estimated VAR models on conditional volatility. Variance decompositions are based on 10-step-ahead forecasts and 200-day rolling windows for all examined periods; VAR lag lengths of the order of 4 or 5 were selected via the AIC.

Figure 1

Plots of daily spot rates and percentage returns for CZK/EUR, PLN/EUR, HUF/EUR, and USD/EUR exchange rates. The sample covers the period from January 1, 1999 to December 30, 2016.

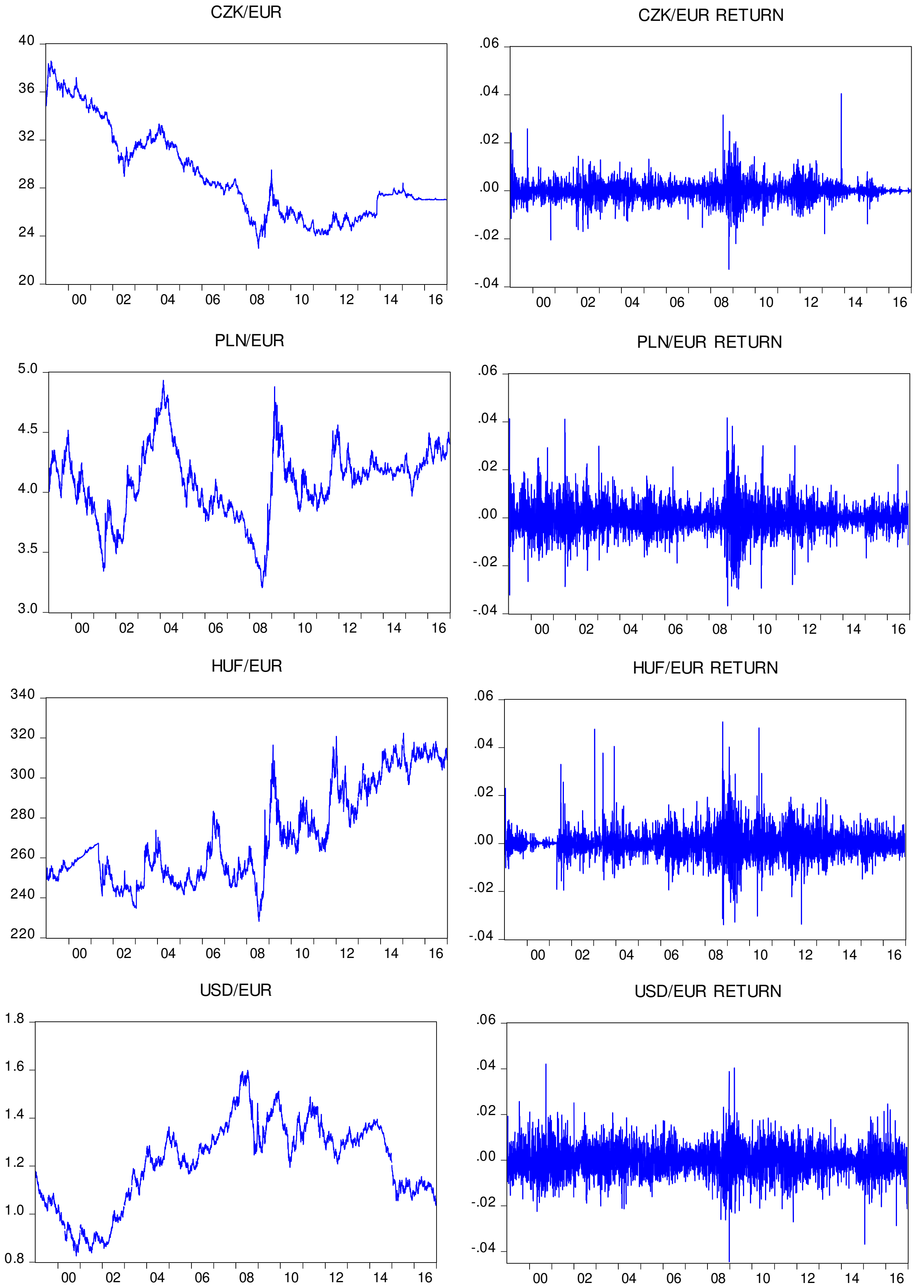
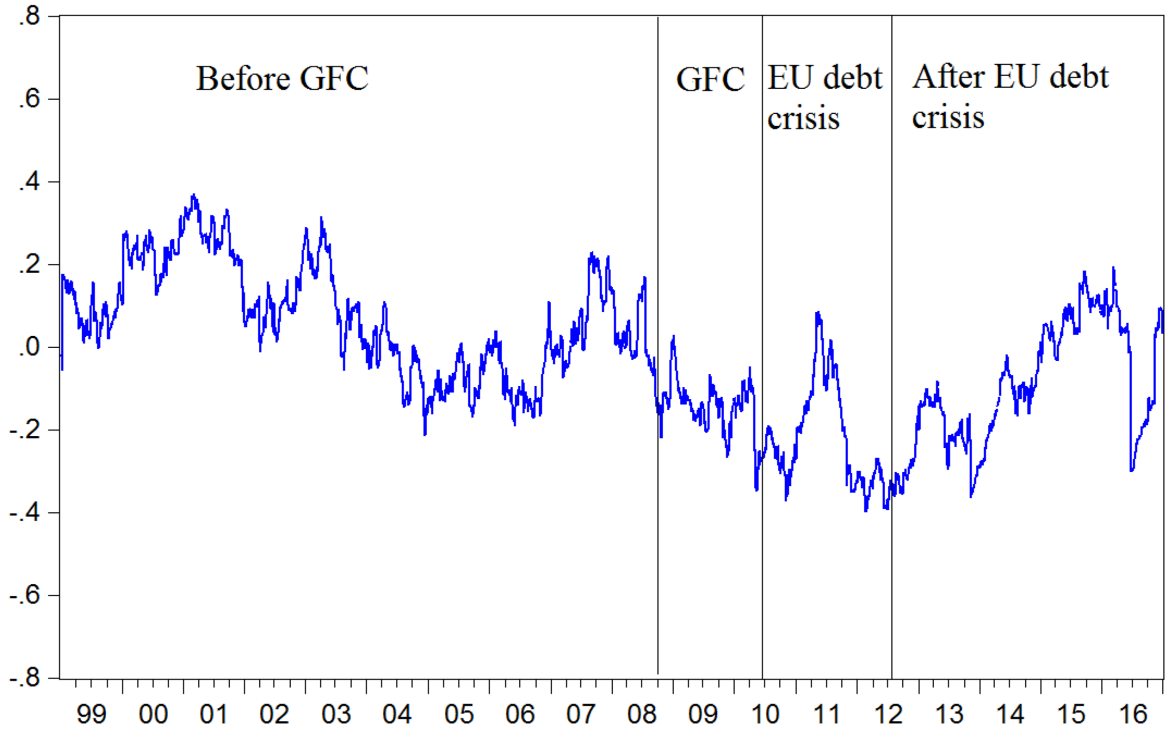


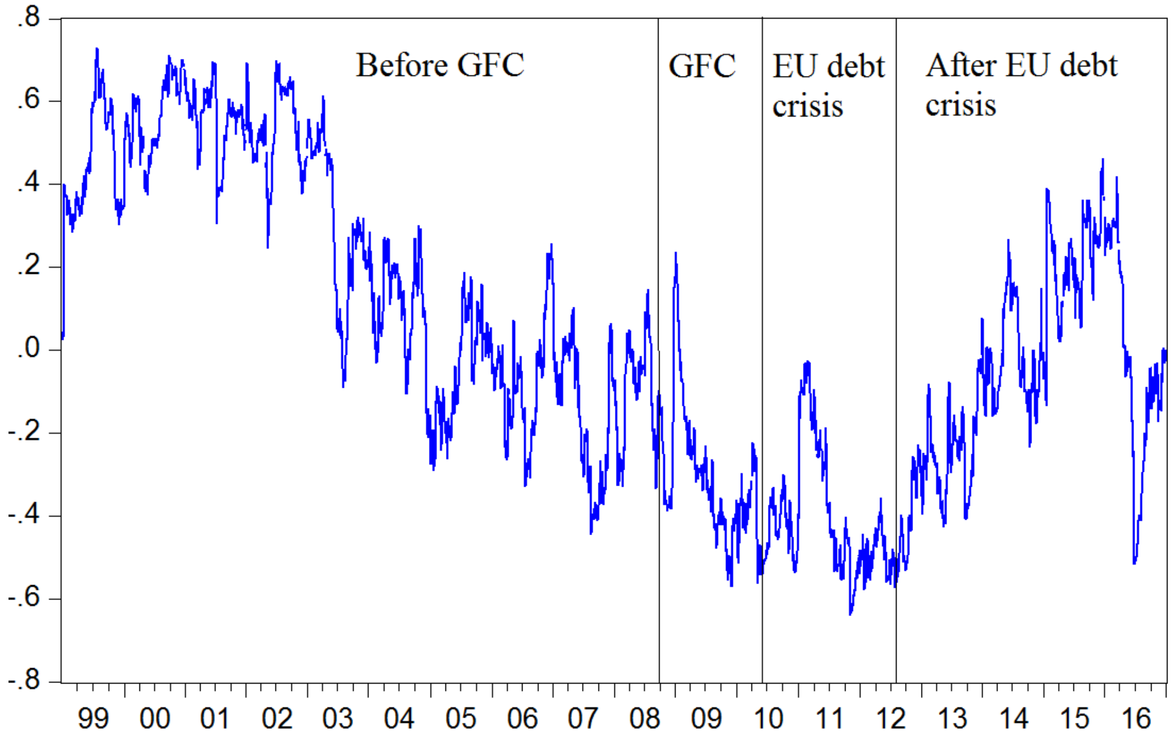
Figure 2

Dynamic conditional correlations.

A: CZK/EUR and USD/EUR in the period of 1999-2016.



B: PLN/EUR and USD/EUR.



C: HUF/EUR and USD/EUR.

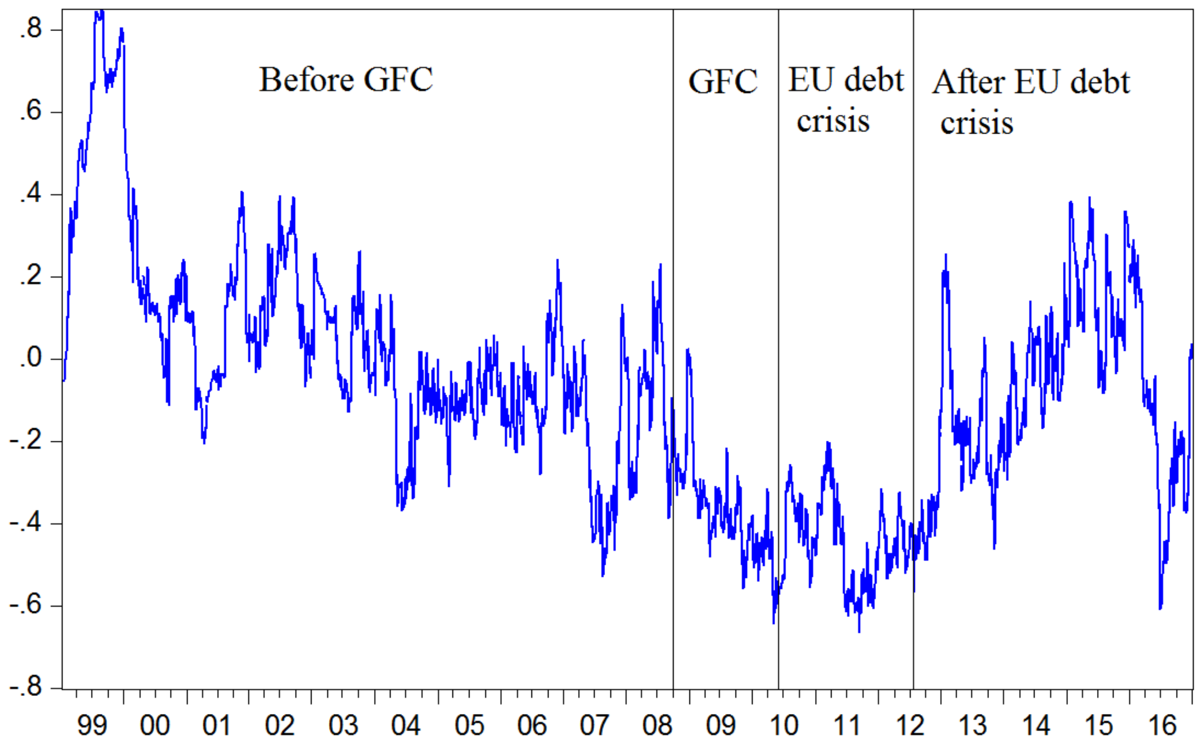


Figure 3: Total volatility spillovers.

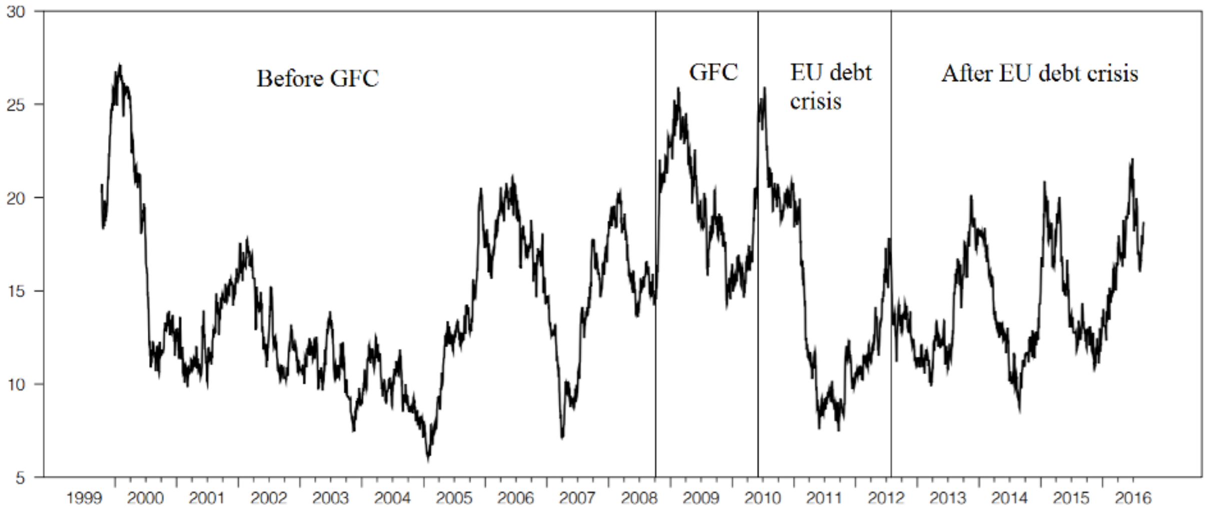
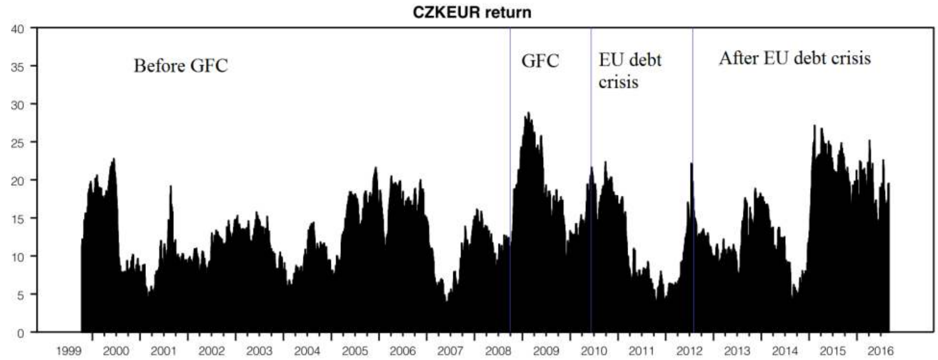
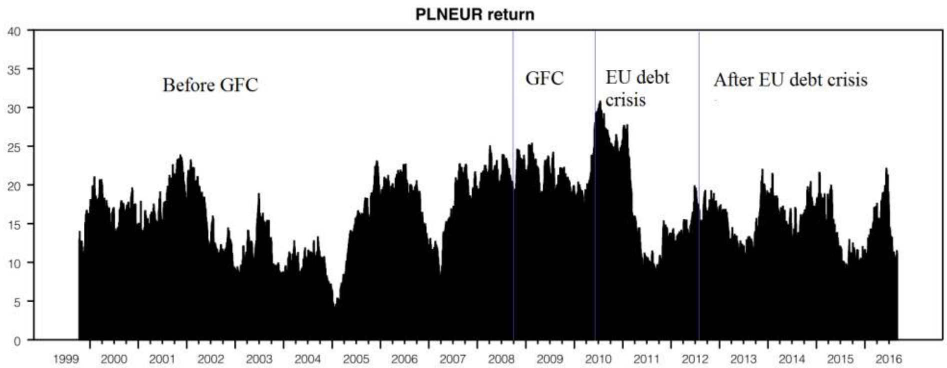


Figure 4: Directional volatility spillovers FROM 4 markets; 200-day rolling windows.

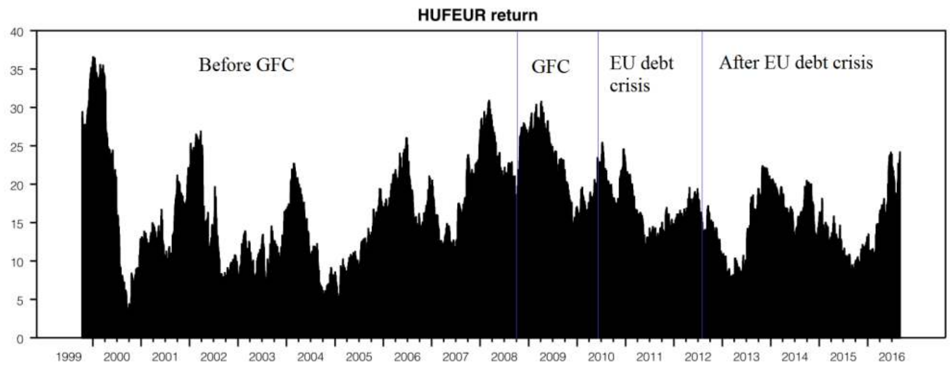
A: CZK/EUR



B: PLN/EUR



C: HUF/EUR



D: USD/EUR

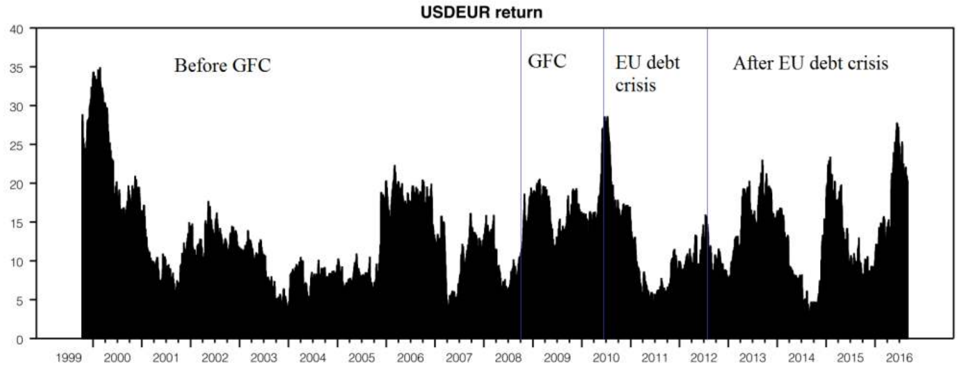
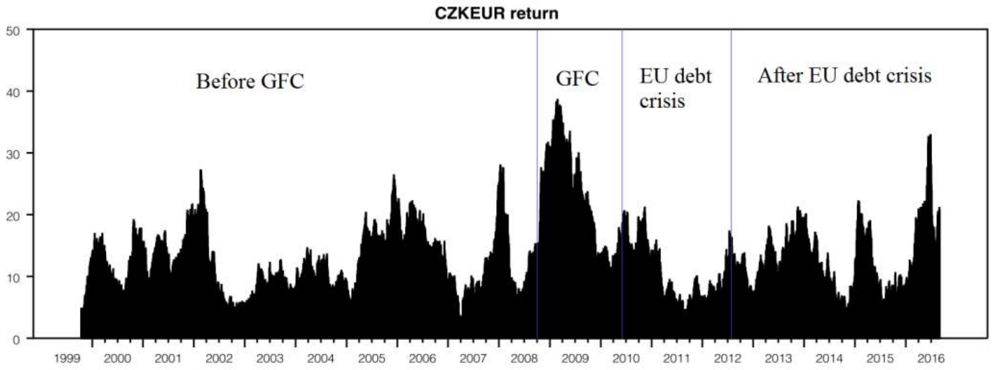
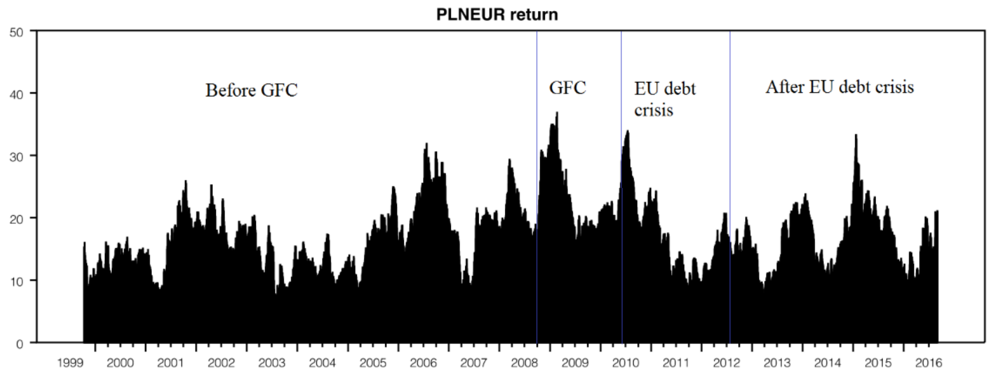


Figure 5: Directional volatility spillovers TO 4 markets; 200-day rolling windows.

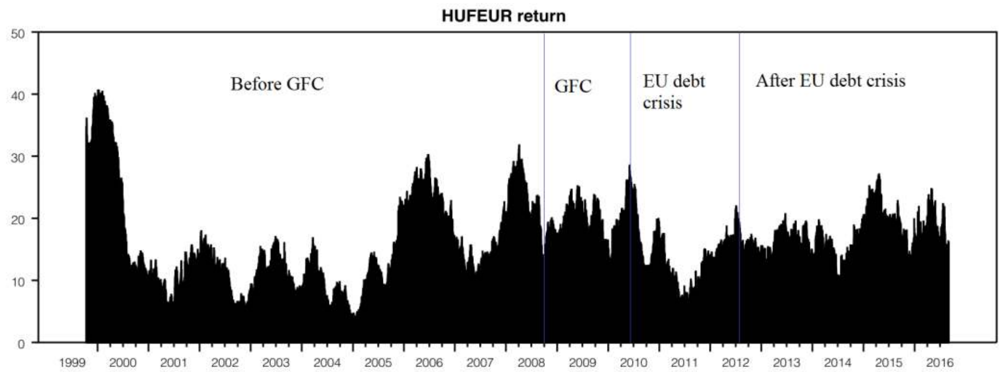
A: CZK/EUR



B: PLN/EUR



C: HUF/EUR



D: USD/EUR

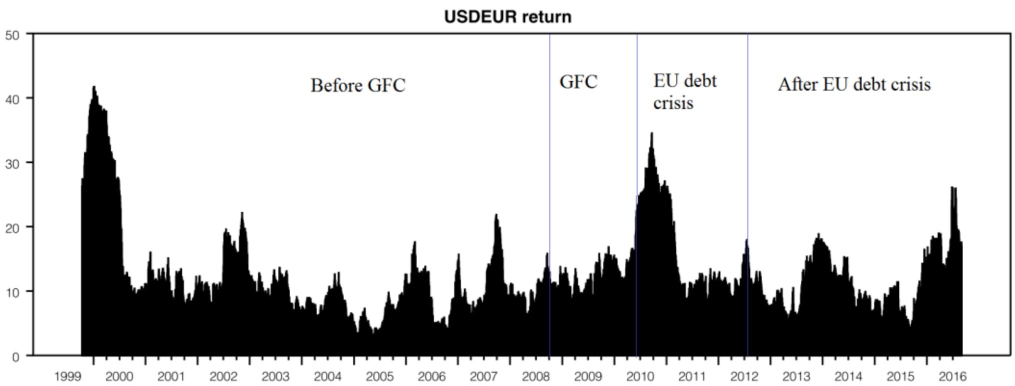
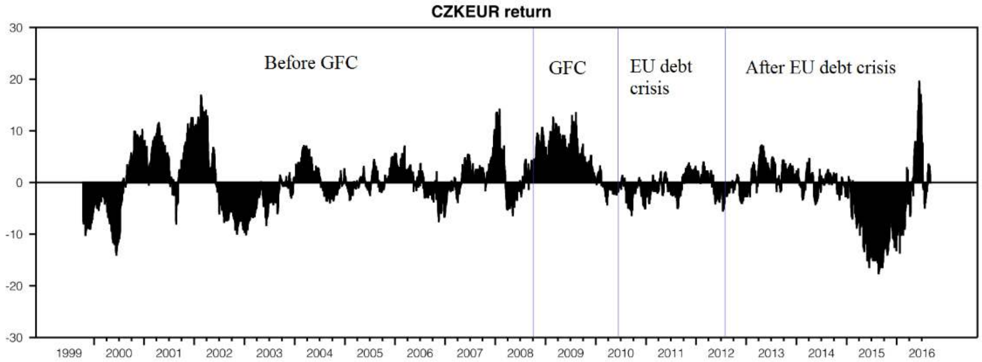
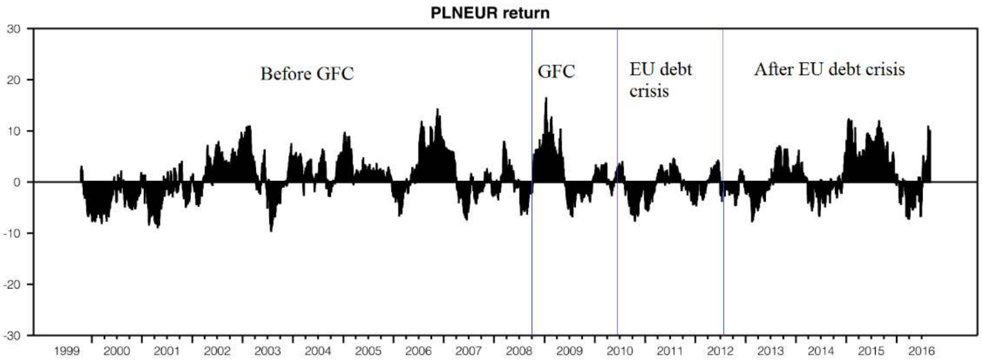


Figure 6: Net volatility spillovers; 4 markets; 200-day rolling windows.

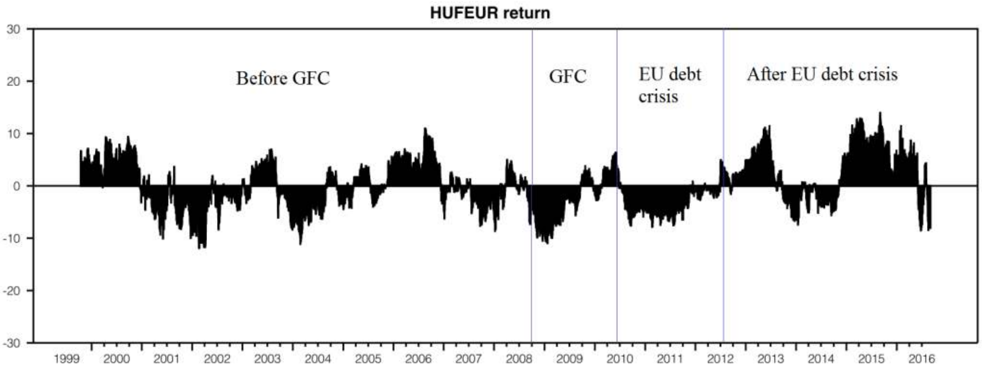
A: CZK/EUR



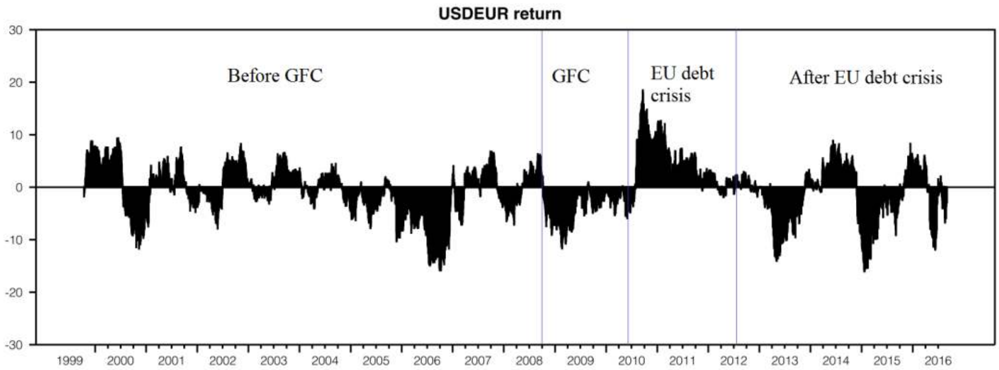
B: PLN/EUR



C: HUF/EUR



D: USD/EUR



Appendix

Table A1

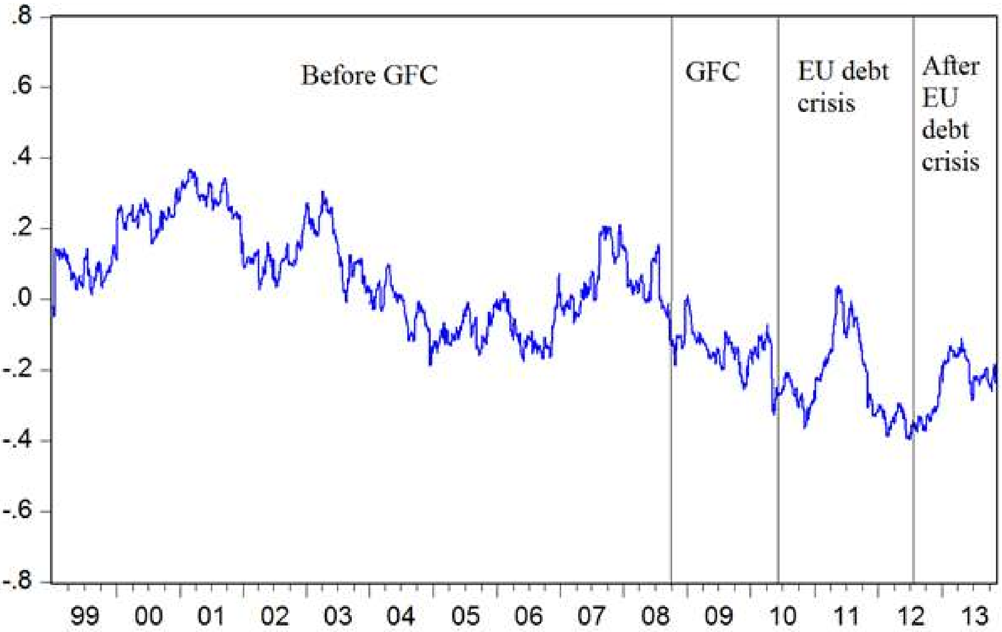
Descriptive statistics regarding the examined exchange returns.

	Before GFC (1.1.1999 - 14.9.2008)				GFC (15.9.2008-30.4.2010)				EU debt crisis (2.5.2010-25.7.2012)				After EU debt crisis (26.7.2012-30.12.2016)			
	CZK/EUR	*PLN/EUR*	*HUF/EUR*	*USD/EUR*	*CZK/EUR*	*PLN/EUR*	*HUF/EUR*	*USD/EUR*	*CZK/EUR*	*PLN/EUR*	*HUF/EUR*	*USD/EUR*	*CZK/EUR*	*PLN/EUR*	*HUF/EUR*	*USD/EUR*
Observations	2484	2484	2484	2484	415	415	415	415	577	577	577	577	1134	1134	1134	1134
Mean	-0.0001	-0.0001	0.0000	0.0001	0.0001	0.0004	0.0003	-0.0001	0.0000	0.0001	0.0001	-0.0002	0.0001	0.0001	0.0001	-0.0001
St. Dev.	0.0035	0.0060	0.0045	0.0062	0.0065	0.0103	0.0099	0.0089	0.0039	0.0062	0.0072	0.0069	0.0023	0.0037	0.0043	0.0054
Skewness	0.4921	0.6023	1.4005	0.1933	-0.0192	0.1840	0.3610	0.0251	-0.0214	0.2594	0.3742	-0.2779	4.4868	0.1546	0.1902	-0.3394
Kurtosis	9.87	7.45	16.12	4.54	5.66	5.04	6.00	6.41	4.09	6.72	7.49	3.19	92.30	5.25	4.36	7.20
ADF	-49.86**	-36.87**	-49.17**	-50.03**	-19.32**	-18.19**	-19.78**	-20.14**	-23.74**	-24.35**	-24.25**	-23.65**	-33.91**	-33.42**	-34.19**	-35.00**
ADF (GLS)	-47.25**	-8.66**	-48.00**	-48.76**	-16.98**	-16.83**	-19.21**	-18.44**	-23.77**	-24.20**	-24.26**	-23.60**	-33.91**	-33.41**	-34.18**	-33.95**
JB	4984.14**	2201.64**	18633**	261.19**	122.52**	74.24**	164.89**	201.33**	28.55**	340.01**	497.89**	8.31*	380600**	243.05**	94.01**	855.08**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Q(10)	7.15	22.72*	18.43*	8.63	10.21	20.71*	10.76	17.33	17.89	16.80	10.68	4.98	9.78	3.92	19.09*	8.98
	[0.711]	[0.012]	[0.048]	[0.567]	[0.423]	[0.023]	[0.377]	[0.067]	[0.057]	[0.079]	[0.383]	[0.893]	[0.460]	[0.951]	[0.039]	[0.534]
Q2(10)	89.704**	753.92**	65.31**	67.482**	214.23**	142.29**	134.65**	97.686**	119.81**	83.979**	8.013	14.997	4.328	110.56**	131.95**	10.381
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.628]	[0.132]	[0.931]	[0.000]	[0.000]	[0.408]
ARCH(5)	11.47**	90.61**	8.48**	7.00**	19.39**	13.41**	8.42**	12.30**	7.32**	6.72**	0.95	1.14	0.17	8.77**	12.37**	1.60
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.444]	[0.335]	[0.973]	[0.000]	[0.000]	[0.157]

Notes: p-values are provided in brackets. JB denotes the Jarque-Bera test for normality. Q (10) and Q2 (10) are Ljung-Box statistics for serial correlations in exchange rate and squared returns, respectively. ADF 5% and 1% critical values are -2.88 and -3.47, respectively. * and ** denote statistical significance at the 5% and 1% levels, respectively

Figure A2

CZK/EUR and USD/EUR in the period of 1999-2013 (without the period involving CNB currency interventions).



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