Exchange rate comovements, hedging and volatility spillovers on new EU forex markets

Evžen Kočenda[a] and Michala Moravcová[b]

Abstract

We analyze time-varying exchange rate co-movements, hedging ratios, and volatility spillovers on the new EU forex markets during 1999M1-2018M5. We document significant differences in the extent of currency comovements during various periods of market distress that are related to real economic and financial events. These imply favorable diversification benefits: the hedge-ratio calculations show all three currencies bring hedging benefits during crisis periods, but at different costs. During calm periods, most of the volatilities are due to each currency's own history. During the distress periods, volatility spillovers among currencies increase substantially and the Hungarian currency assumes a leading role.

JEL: C52, F31, F36, G15, P59

Keywords: Exchange rates; new EU forex markets; volatility; DCC model; volatility spillover index; portfolio weights and hedge ratios; EU debt crisis; global financial crisis

a Institute of Economic Studies, Charles University, Opletalova 26, 110 00, Prague, Czech Republic. CESifo, Munich; IOS, Regensburg; Phone: (+420) 222.112.321; Fax: (+420) 222.112.304; E-mail: evzen.kocenda@fsv.cuni.cz

b Institute of Economic Studies, Charles University, Opletalova 26, 110 00, Prague, Czech Republic. Phone: (+420) 734.256.666; E-mail: moravcovamichala@gmail.com

We are grateful for helpful comments from Jonathan Batten, David Kemme, Vasilis Pappas, and participants at several presentations. The usual disclaimer applies.

1. Introduction and motivation

The evidence from mature forex markets shows that interdependencies and volatility spillovers relate to decisions of central bank interventions (Menkhoff, 2013), impact international trade (Rose, 2000), influence the stock prices of multinationals (Baum et al., 2001), and directly affect risk management and portfolio diversification (Kanas, 2001; Garcia and Tsafack, 2011; Fengler and Gisler, 2015). The analysis of such interdependencies and volatility spillovers facilitates to deepen our understanding of post-crisis financial integration (Antonakakis, 2012). Naturally, questions arise regarding how interdependencies and spillovers evolve on the emerging forex markets that are much less researched but attract substantial capital inflows in foreign currencies (Ahmed and Zlate, 2014).

Based on theoretically and empirically grounded patterns found in developed forex markets, we analyze the complex dynamics of several emerging European Union (EU) forex markets within themselves as well as with respect to the rest of the world. Surprisingly, the new EU forex market remains outside the research mainstream, even though the currencies of three advanced new EU member states (the Czech Republic, Hungary, and Poland) score highly in terms of their attractiveness to risk-capital investors (Groh and von Liechtenstein, 2009). In addition, these currencies have gained particular importance as the three countries have become more integrated into the EU economy following their 2004 accession (Hanousek and Kočenda, 2011), especially via their trade and banking sector links (Gray, 2014). Further, the three currencies are also quite important for diversifying mutual and hedge fund portfolios that are primarily domiciled in developed markets (Jotikasthira et al., 2012).[1]

Hence, we augment the field literature with analyzing the extent and evolution of interdependencies and connectedness on the new EU forex markets. Specifically, we (i) analyze time-varying co-movements among the three currencies, (ii) compute their hedge ratios and portfolio weights, and (iii) study how volatility spillovers

[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).

propagate among them. We calculate volatility co-movements and spillovers between new EU forex markets and the rest of the world by employing the dollar/euro exchange rate as the world forex benchmark. We also estimate mutual spillovers between new EU currencies to provide assessment whether the investors should consider new EU forex market as a single unit or whether it makes a difference to recognize volatilities of the individual currencies along with their directions and magnitudes.

In addition to being motivated by the lack of quantitative research, our interest in the dynamics of the new EU forex markets is motivated by the aim to assess various theoretically and empirically grounded patterns found in developed forex markets that are related to the three types of assessments we perform.

First, investors tend to mimic other investors' behavior, described as herding behavior, which has been observed in a number of activities, including investments on the forex market (Tsuchiya, 2015) and the stock market (Bohl et al., 2017). This time-varying herding behavior can be indirectly observed from correlations between exchange rates that we compute. Specifically, investors tend to follow the crowd when times are uncertain; they begin to doubt their own judgment and run in herds. This behavior can be observed in the U.S. financial market through rising correlations between financial assets. Further, the assessment of time variations in the correlations between different assets has critical implications for asset allocation and risk management because weak market linkages offer potential gains from international diversification (Singh et al., 2010).[2] Hence, we analyze the degrees and dynamics of comovements among currencies based on the Dynamic Conditional Correlation (DCC) model developed by Engle (2002).

Second, in his optimal portfolio theory, Markowitz (1991) describes how risk-averse investors can construct portfolios to optimize or maximize expected return based on a given level of market risk. We assess this idea by using the conditional variances and covariances estimated from the DCC model to compute hedge ratios and portfolio weights for the three individual currencies in an optimal portfolio. We also account for different periods of distress in the market. Our results may help foreign investors recognize whether new EU countries should be treated as a whole or

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

whether it is preferential to select assets individually from each country to improve portfolio diversification.

Third, Hau (2002) argues that more open economies exhibit less volatile real exchange rates. The three countries under study are very open economies. We indirectly assess the volatility of their currencies by showing the nature and extent of volatility spillovers among the currencies. Further, analysis of the extent and nature of volatility spillovers in new EU forex markets is performed because volatility and its spillovers across currencies affect decisions about hedging open forex positions and may exacerbate the nonsystematic risk that diminishes the gains from international portfolio diversification (Kanas, 2001). In this respect, Menkhoff et al. (2012) accentuate the role of innovations in global forex volatility on a liquidity risk. Further, volatility represents a systematic risk that is considered tu underline carry-trades.[3] We analyze volatility spillovers using a generalized version of Diebold and Yilmaz's (2012) spillover index (DY index).

Our analysis is also relevant from the perspective of the European forex market and its recent financial turmoil. The EU forex market underwent a fundamental change when the euro became a joint currency for euro-area members in 1999. The euro's introduction also altered the relative importance and nature of interdependencies among major world currencies on the global forex market (Antonakakis, 2012), as the euro became the second most–traded currency in the world (BIS, 2016). 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, and for the countries that joined the EU in 2004 and later, euro adoption became a goal.

Both mature and emerging forex markets experienced another important change: on September 15, 2008, the collapse of U.S. investment bank Lehman Brothers brought volatility and distress to the financial markets, followed by a credit crunch. Financial contagion spread from the USA and was soon followed by the European debt crisis. Both the global financial crisis (GFC) and the sovereign debt crisis in Europe (EU debt crisis) renewed interest in the nature and extension of contagion effects among financial markets (Aloui et al., 2011). The effect of the GFC

[3] Carry trade represents investment in high-interest currency based on the opportunity that emerges due to the failure of uncovered interest rate parity.

and the EU debt crisis spread from the source countries to the rest of the world. The financial contagion and turbulence were transmitted from developed to emerging markets (Gray, 2014).

Our analysis is performed on daily data from 1999 to May 2018. The span of our dataset begins with the introduction of the euro and covers periods of relatively calm development as well as 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 when both previous crises subsided (2012-May 2018).

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 U.S. dollar tend to decrease prior to the GFC and the EU debt crises. Once economic and financial disturbances subside, the correlations begin to rise to pre-crisis levels. This behavior should be beneficial for portfolio diversification. However, investors pay a price: our results indicate that hedging during the GFC and the EU debt crisis costs more than before or after the crisis. We assess volatility and interdependencies on the new EU forex markets via spillovers. Most of the time, own-currency volatilities explain a substantial share of exchange rate 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. Among the three currencies, the Hungarian forint is dominant 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

Volatility in exchange rates has important economic implications. For example, it influences import and export price uncertainty and thus affects international trade flows (Rose, 2000). Chowdhury and Wheeler (2008) demonstrate that shocks to exchange rate volatility have an effect on FDI. Baum et al. (2001) analyze the impact of exchange rate volatility on multinational companies' profitability and consequently on the stock prices of these companies. Aghion et al. (2009) indicate that exchange rate volatility can influence productivity growth. Exchange rate volatility has also adverse impact on industrial production and employment (Belke and Gros, 2002).

Volatility has become the subject of broad research since Bollerslev (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. Recognition of volatility comovements and spillovers in the financial markets is fundamental for systemic risk identification (Mensi et al., 2017). Such recognition is also relevant in the context of the shock transmission mechanism linking financial markets and the real economy.

Increasing integration of financial markets supported by globalization requires examining volatility co-movements and spillovers between developed and emerging markets. A substantial part of the literature has primarily focused on developed forex markets (McMillan and Speight, 2010; Boero et al., 2011). Emerging markets are less examined with very little attention paid to new EU markets. Pramor and Tamirisa (2006) examine volatility trends in the Central and Eastern European currencies. They demonstrate 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 present a high degree of comovements in short-term fluctuations among the exchange rates of the Czech Republic, Poland and Hungary. Bubák et al. (2011) 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 2003-2009. They find that during the pre-2008 period, the volatilities of the Czech and Polish currencies are affected chiefly by their own histories but each of the three new EU currencies is characterized by a different volatility transmission pattern.

To the best of our knowledge, our analysis is the first to examine volatility comovements and spillovers between the U.S. dollar and new EU markets shortly before the GFC, during the GFC, during the EU sovereign debt crisis, and after both distress periods. In addition, we also calculate time-varying hedge ratios to assess how to minimize the risk of the new EU currencies portfolio. Our results show that international investors may enhance diversification benefits from allocating part of their portfolio funds to new EU exchange market. We confirm the importance of the new EU currencies for international investors in terms of diversification benefits by moving part of their portfolio to those currencies. In terms of volatility transmission, the highest level of the total volatility spillover index on new EU FX markets is observed during the GFC. At that time, cross-currency volatility rises, and own-currency volatility declines. The Hungarian economy suffered considerably from the GFC, which led to volatility propagation from the Hungarian forint to other new EU currencies.

3. Data, methodology and hypotheses

3.1 Dataset and analyzed periods

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 U.S. dollar against the euro (USD/EUR).[4] The time span runs from the euro's introduction on January 1, 1999, to May 31, 2018, and contains 4,970 observations. Data are quoted at 2:15 p.m. (C.E.T). Time series were downloaded from the ECB online database. 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

[4] 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 comovements 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.

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.

Further, 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 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.

Our intention is to analyze the data during different periods of distress, such as the GFC and the European sovereign debt crisis. For this purpose, we divide the data into four subsamples reflecting (i) the two major financial and economic events that (ii) are also mirrored in structural breaks present in the data.[5] The coincidence aligns with the empirical evidence that structural changes in financial series can be due to various economic events (Andreou and Ghysels, 2009) or shifts in economic policy (Pesaran et al., 2006). Hence, the first sub-sample covers the period prior to the GFC (January 1, 1999-September 14, 2008), the second period represents the GFC's key phase (September 15, 2008-April 30, 2010) and the third period covers the EU debt crisis (May 3, 2010-July 26, 2012). The fourth subsample captures the period following the EU debt crisis until the end of our sample span (July 27, 2012-May 31, 2018).[6]

The GFC's beginning is associated with the Lehman Brothers' bankruptcy on September 15, 2008, which is in accord with the test as well as practice in the literature (Frankel and Saravelos, 2012). 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

[5] We applied the Bai-Perron (1998, 2003) test to detect structural breaks in conditional variances (of the exchange rates returns) derived via the DCC-GARCH described in the Section 3.2. The test shows the dominant structural break in 2008 consistent with the beginning of the GFC. Regarding the EU debt crisis, the test suggests different break points for individual new EU exchange rates. The differences in the date break estimates are not uncommon: Bai and Perron (1998) show that in the presence of multiple breaks the least squares estimator converges to a global minimum that coincides with the dominating break. For the sake of consistency, we use the common dates to limit boundaries of distress/no-distress intervals that are grounded in the well-established economic events described in the text.

[6] As a complement to the previous test, we performed the Chow (1960) breakpoint test. The test evidences structural breaks in conditional correlations of the neighboring four sub-periods defined with respect to the GFC and European debt crisis (Table A2).

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.[7] The rest of the data cover the post-EU debt crisis period.

3.2. Dynamic Conditional Correlation GARCH (DCC-GARCH)

We use the DCC model of Engle (2002) to assess the evolution of comovements 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 studied. The DCC model offers several advantages relative to simple correlation analysis. First, it is parsimonious compared to many multivariate GARCH models.[8] Second, the DCC model is flexible because it enables the estimation of time-varying volatilities, covariances and correlations of various assets over time.[9]

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

[7] 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&P, MIB 5.6% (12.4%), CAC40 4.1% (7.1%), and DAX 2.8% (6.0%).

[8] 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.

[9] Intentionally, we do not use an asymmetric DCC model. Baruník et al. (2017) show that different event types are characterized by different types of volatility spillovers 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 heavy asymmetries to occur in individually examined periods.

transformed by their standard deviation from the first stage are used to construct a conditional correlation matrix.

Under the absence of serial correlation the exchange rate return (r_t) in the mean equation follows a random walk and the composition of the conditional covariance matrix is:

$$H_t = D_t R_t D_t \tag{1}$$

$$D_t = diag\,(h_{iit}^{\frac{1}{2}}, \ldots, h_{NNt}^{\frac{1}{2}})', \tag{2}$$

$$R_t = diag\left(q_{ii,t}^{-\frac{1}{2}}, \ldots, q_{NN,t}^{-\frac{1}{2}}\right) Q_t\, diag\left(q_{ii,t}^{-\frac{1}{2}}, \ldots, q_{NN,t}^{-\frac{1}{2}}\right) \; or \; \rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}\, q_{jj,t}}} \tag{3}$$

where h_{iit} can be defined as any univariate GARCH model.[10]

In (3), $Q_t = (q_{ij,t})$ is the ($N \times N$) symmetric positive definite matrix given by

$$Q_t = (1 - \alpha - \beta)\overline{Q} + \alpha u_{t-1} u_{t-1}^{'} + \beta Q_{t-1} \tag{4}$$

where $u_t = (u_{1t}, u_{2t}, \ldots, u_{Nt})$' is the N * 1 vector of standardized residuals; $\overline{Q}$ 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).[11]

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.

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

$$\beta_{ij,t} = h_{ij,t}/h_{jj,t}\,, \tag{5}$$

---

[10] The AR(1)-GARCH (1,1) model is employed if serial correlation is presented in the residuals of the GARCH (1,1) model.
[11] A multivariate Student's *t* error distribution was also employed, but it did not improve our results.

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:

$$w_{ij,t} = \frac{h_{jj,t} - h_{ij,t}}{h_{ii,t} - 2h_{ij,t} + h_{jj,t}} \ . \tag{6}$$

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:

$$w_{ij,t} = \begin{cases} 0, & if\ w_{ij,t} < 0 \\ w_{ij,t}, & if\ 0 \leq w_{ij,t} \leq 1 \\ 1, & if\ w_{ij,t} > 1 \end{cases} \ . \tag{7}$$

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 (2009, 2012) spillover index based on the generalized vector autoregressive (VAR) variance decomposition is used. The p-order, N-variable VAR model with the vector of independently and identically distributed errors of four examined endogenous variables (exchange rates - CZK/EUR, PLN/EUR, HUF/EUR, USD/EUR) is applied.

Variance decompositions in Diebold and Yilmaz index (2012) are invariant in terms of the variable ordering. In this case, the H-step-ahead forecast error variance decomposition is defined as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{ii}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma A_h' e_j\right)} \ , \tag{8}$$

where Σ is the variance matrix for the error vector ϕ, σ_{ii} is the standard deviation of the error term for the ith equation, and e_i is the selection vector, with a value of one for the ith 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 $\left(\sum_{j=1}^{N}\theta_{ij}^{g}(H) \neq 1\right)$. Each element of the decomposition matrix is normalized by dividing it by the row sum:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)}, \tag{9}$$

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

Using normalized elements of the decomposition matrix of equation (9), the total volatility spillover index is constructed as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\theta_{ij}^{g}(H)} * 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N} * 100. \tag{10}$$

The 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 further 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:

$$S_{i \xleftarrow{g} j}(H) = \frac{\sum_{\substack{j=1 \\ i \neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} * 100. \tag{11}$$

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:

$$S_{i}^{g}(H) = S_{i \xrightarrow{g} j}(H) - S_{i \xleftarrow{g} j}(H). \tag{12}$$

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

The dynamics of the studied exchange rates are presented in Figure 1. During the examined time period from January 1999 to May 2018, the Czech koruna appreciated by 30 percent and the Hungarian forint depreciated by 20 percent against the euro. The Polish zloty oscillated around a value of 4.0. The USD/EUR exhibited various patterns. First, the U.S. dollar appreciated against the euro from 1999 to 2002 and reached the value of 0.85. Later, the euro appreciated against the U.S. dollar and reached the value of 1.58 at the GFC's start in fall 2008. After the GFC, the euro was continuously losing its value until reached the minimum against the U.S. dollar at the level of 1.04 in the beginning of 2017. Since then euro has been slowly appreciating and came back to 1.20 level against the U.S. dollar in 2018.

Descriptive statistics of the examined exchange rates are presented in the Appendix (Table A1). An analysis of percentage returns shows that all examined forex markets exhibit the largest volatility in 2008 when the GFC began (see the values of standard deviation in Table A1 and depiction of returns in Figure 1). Otherwise, the standard deviations of the four exchange rates decrease after the EU debt crisis, which demonstrates lower levels of contagion and financial distress. The only notable exception is a single sizable spike in the CZK/EUR daily returns observed in 2013 (Figure 1). The volatility spike is endogenous in nature and is associated with the introduction of the "exchange rate commitment" and ensuing currency interventions by the Czech National Bank.[12]

In addition, the average daily returns are very similar across all four examined exchange rates and close to zero. When examining each period separately, the largest standard deviation in Table A1 (and the highest volatility) is associated with the Polish zloty (PLN) during the GFC. On the other hand, Czech currency exhibits the lowest standard deviation in each individually analyzed period. In other words, the Czech koruna (CZK) is the least volatile currency of the three new EU currencies

[12] The CNB practiced an "exchange rate commitment" (constraining exchange rate regime) 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. The measure was similar to the "capping" practiced by the Swiss National Bank.

examined. Hau (2002) shows that more open economies have less volatile real exchange rates. We confirm this finding. Out of the three examined countries, Poland has the least open economy in terms of the net export to GDP ratio and the most volatile currency during the GFC.

Further, the skewness and excess kurtosis indicate a non-normal distribution of examined time series; this is also confirmed by the *p*-value of the Jarque-Bera test, which suggests that the null hypothesis may be rejected at the 1% significance level. 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, which aligns with their highest values of standard deviation from all examined exchange rates. The CZK/EUR skewness and kurtosis values temporarily increased after the Czech central bank launched currency interventions in 2013.

Finally, the Ljung-Box test Q and Q^2 statistical results are presented. The serial correlation in squared returns is confirmed for almost all the time series and implies the presence of non-linear dependencies. Moreover, according to Engle's ARCH-LM statistics, an ARCH effect exists 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 the application of GARCH-type models.[13]

4.2. Exchange rate comovements

The results of the time-varying exchange rate comovements based on the DCC-GARCH model described in Section 3.2 are presented in Table 1.

As a common pattern, the new EU exchange rates behave homogenously in individually examined time periods and exhibit common behaviors in terms of comovements 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

[13] Both the HUF/EUR and USD/EUR values for during the EU debt crisis and the CZK/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 the samples. The absence of ARCH effects found in the CZK/EUR after the EU debt crisis 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 intervention period on April 6, 2017.

– 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).[14] These results suggest that new EU currencies behave mutually similarly, but differently from the world-leading forex flow represented by USD/EUR during crisis period. 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).

Based on our reasoning in Section 3.1, we calculate conditional correlations for each time period separately and report them in Table 1. Further, we assess whether the difference in the time-varying magnitude of two conditional correlations (ρ) is statistically significant. In the same way as Corsetti et al. (2005), 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 (neighboring time periods) and report the results in Table 2. Based on the results of the test, we reject the null hypothesis for all period-pairs and all new EU currencies.[15] The results in Table 2 provide evidence that dynamic conditional correlations are not constant and their magnitudes differ among the four examined time periods. The above results enable us to reject Hypothesis 1.

We also provide a robustness check of the breaks in correlation as in Chiang et al. (2007). We use three mutually exclusive dummy variables taking value of 1 during three sub-samples: the GFC ($DM_{1,t}$), the EU debt crisis ($DM_{2,t}$), and after the EU debt crisis ($DM_{3,t}$), to construct the regression model:

[14] 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 18.5 years (January 1999-May 2018). In this model, the individual periods such as the GFC and the EU debt crisis are reflected by the dummy variables. As a result, the graphs of pair-wise conditional correlations representing the whole period of 18.5 years show the same behavior as conditional correlations calculated and representing partial time periods.

[15] In the Fisher *Z*-Transformation the correlation coefficients are converted to normally distributed *Z* variables (Z_0, Z_1) by this formula: $Z_0 = \frac{1}{2}\ln\left[\frac{1+\rho_0}{1-\rho_0}\right]$ and $Z_1 = \frac{1}{2}\ln\left[\frac{1+\rho_1}{1-\rho_1}\right]$, 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*-values indicate that ρ_0 is larger than ρ_1; negative *z*-values demonstrate that ρ_0 is smaller than ρ_1. The critical values for the Fisher *Z*-test with 1.5 and 10% statistical significance are 1.28, 1.65 and 1.96, respectively.

$$\rho_{ij,t} = \sum_{p=1}^{P} \phi_p \rho_{ij,t-p} + \sum_{k=1}^{3} \alpha_k \, DM_{k,t} + e_{ij,t}. \quad (13)$$

In (13), $\rho_{ij,t}$ is the conditional correlation of new EU exchange rates and USD/EUR from the DCC model; the lag length is calculated for each pair-correlation individually based on the AIC criterion, and $DM_{k,t}$ represents the above dummy variables. Based on the coefficients reported in Table A3, the dummy variable for the GFC and European debt crisis is statistically significant for all correlations. The ARCH effects are absent in residuals (see row ARCH (5) in Table A3).

The previous robustness check is a less direct approach than the former application of the Fisher *Z*-transformation. However, the outcomes of the Fisher *Z*-transformation are corroborated by this robustness check and imply that conditional correlations are not stable over the time. The results further support our empirical strategy to examine conditional correlations separately for several distress and no-distress periods—the specific results are shown presently.

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. Differing patterns of comovements in the forex market are revealed. 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 0.5 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 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 compared to the GFC period indicates 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 comovements in new EU forex markets during both recent crises. Negative values of correlation coefficients indicate the absence of herding behavior on the currency market during the GFC. In the other words, investing in new EU currencies provides investors with good diversifying opportunity against the U.S. dollar. The findings are in line with the results of Miyajima et al. (2015), who show that (i) benefits from diversification in emerging market local currency bonds have increased since 2008, and (ii) emerging market government bonds (including those of Hungary and Poland) have been resilient to global risk shocks. Gilmore and McManus (2002) also confirm that US investors can obtain benefits from international diversification into Central European equity markets. Assets' liquidity is also an important factor in evaluating investment strategy. Should the lower traded volume prevent investors from considering the diversification benefits of new EU exchange market? Menkhoff et al. (2012) show that liquidity risk matters less than volatility risk for pricing returns.

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 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 the EU debt crisis. 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. The correlations slowly return to pre-crisis levels again in the second half of 2016. However, they did not stay there for a long time and felt back to the negative territory in early 2017, when several events increased global uncertainty. First, the US president Donald Trump applied steps heading to US trade protectionism, including the country's withdrawal from the NAFTA agreement. Second, the Fed started to tighten monetary conditions with three interest rates hikes within one year. Third, the ECB terminated the period of unconventional expansionary monetary policy by approaching the cut of monetary stimulus for the first time since the EU debt crisis.

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 A1 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; the exceptions are CZK/PLN and CZK/HUF after the EU debt crisis. 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 0.3972. Hence, in 1-euro portfolio, on average, 0.3972 euros should be invested in the CZK, and 0.6028 euros should be invested in the HUF. Lower share of the Czech koruna in the portfolio can be explained by the CZK appreciation after the CNB terminated currency interventions on the FX market. A regular recalculation of portfolio weights is inevitable for investors who want to reach the maximum expected return at a certain level of risk. Attaining the optimal portfolio weights for the CZK/HUF prior to the GFC and after the EU debt crisis means decreasing the weight of the CZK by 25.7 percent and increasing the weight of the HUF by 29.6 percent.

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 a 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. A 1-euro long position in the CZK can be hedged with a 0.43 short position in the PLN. After the EU debt crisis, we need to open only the short position in the PLN of 0.32 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 examined periods except during 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. Volatility spillovers

The results of volatility spillovers based on the Diebold and Yilmaz (2012) 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.[16] This way we provide two outcomes. First, we examine spillovers in a broader context of how spillovers come from the rest of the world to the new EU markets and vice versa. In our analysis the dollar/euro exchange rate represents the world forex market – this aggregate proxy is the most traded currency pair in the world representing the two world largest economies. Second, we examine forex spillovers among new EU countries that share historically strong trade relations and belong to the Visegrad Four (V4) group with economically important role in the Central and Eastern Europe (CEE).[17] Detecting and quantifying volatility spillovers between the V4 nations can help central bank policy makers to coordinate their approach if one of the currencies suffers from increased volatility. Stable currency environment (i) is

[16] 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*.

[17] The Visegrad Four group consists of the Czech Republic, Poland, Hungary and Slovakia. Slovak currency is not involved in our research, because the country adopted the euro in 2009.

crucial to achieve economic stability encompassing both stable prices and real growth immune to wide swings, and also (ii) brings benefits for international investors who consider new EU countries highly attractive in terms of number of funds they allocate there (Jotikasthira et al., 2012).

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 in early 2008, in 2009, and in 2017. The two peaks in 2008 and 2009 correspond to the GFC period; a similar pattern is observed by Bubák et al. (2011) also show increase in volatility spillovers among the new EU forex markets during periods of market uncertainty.

After the EU debt crisis, the most significant events have occurred recently, especially in 2017. We observe a notable increase in the spillover index in 2017 after Donald Trump was inaugurated as the U.S. president and withdrew the United States from the Trans-Pacific Partnership. During 2017 as well as in 2018, he continued working on policies leading to diminishing the U.S. trade deficit with foreign partners. However, his steps towards the U.S. trade protectionism became major concern for politicians, international institutions, investors and multinational companies. Further, Jawadi and Fitti (2017) suggest that U.S. fiscal stimuli planned by the Trump administration may lead to faster rise in the U.S. interest rates. This could increase the rates in other countries through a contagion effect and induce more volatility on financial markets.

The inflation acceleration in the United States resulted in the series of interest rate hikes in 2017. Fed increased interest rates three times during 2017. This was the first time for the Fed to apply more than one interest rate increase within one year since the end of the GFC. The ECB also signaled its plans to tighten monetary policy for the first time since the EU debt crisis. It decreased the monthly amount of the asset purchase program (APP) from 80. to 60 billion euros and indicated its plans to end the quantitative easing program (QE) before the end of 2018. The Czech National Bank (CNB) decided to end its forex intervention program in 2017 and increased interest rates two times in that year. All these important events poses capacity to impact financial markets, and as a result the volatility on financial markets rose and spillovers increased in 2017.

The diagonal values ($i = j$) of the total spillover index presented in Table 4 are higher than off-diagonal values ($i \neq j$). 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 zloty-forint during the EU debt crisis. These findings are consistent with those of Antonakakis (2012), who find that forex market volatility exhibits bidirectional volatility spillovers rather than unidirectional volatility spillovers between the euro and set of developed market currencies. However, other markets might exhibit entirely different behavior. For example, Rodríguez et al. (2015) show that shocks across countries explain major part in the total volatility spillover index on European sovereign bond markets.

When the four individually examined time periods are considered, the highest value of the index is observed during the GFC reaching the value of 21.6 percent (see Table 4); second highest value is reached in the beginning of 2017. 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.[18] 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 the 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 a similar way, Gray (2014) recognizes greater

[18] 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.

turbulence on the new EU forex market during the GFC than in tranquil periods and finds that propagation of currency turbulences is not linear.

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. Of the three examined new EU countries, the Hungarian economy suffered most during the GFC and EU debt crisis. One of the main problems Hungary faced was its depreciating currency. The Hungarian forint declined against the Swiss franc by 60 percent from 2008 and 2012, which enormously increased the household debt burden of mortgages denominated in Swiss francs. Moreover, the worsening economic situation in the country further increased selling pressure on the forint. The results showing diffusion of the contagion from Hungary to surrounding countries via currency spillovers may serve as useful information for policy makers. Contrary to the Hungarian forint, the Czech koruna transmits the lowest proportion of volatility prior to the GFC and during the EU debt crisis. From another 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.[19] 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 (11) 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 currencies TO each individual currency for all three periods examined.[20] These figures depict the development of volatility patterns over the research period. According to Figures 4 and 5, the Hungarian forint retains its leading role in volatility transmission, as directional volatility spillovers reach 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.

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

[20] Figures 4 and 5 represent dynamic versions of the "Contributions to others" row and the "Contributions from others" column in Table 4, respectively.

Finally, Figure 6 shows net volatility spillovers from/to each of the four examined exchange rates computed using equation (12) 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, as well as in 2017 when the U.S. president Donald Trump begun to take steps for protecting the U.S. companies. The Hungarian forint is the most vulnerable currency during the GFC and the EU debt crisis, as it is a net volatility receiver during much of the 2008-2012 period. The Hungarian forint also suffered from higher volatility coming from outside of the market in 2016 and 2017. Finally, the Czech koruna became the source of volatility in 2017, when the Czech National Bank concluded its currency interventions and led the koruna trade freely. On the other hand, during the large part (2014-2016) of the interventions' period the Czech koruna was mainly volatility receiver. The above findings further support the rejection of Hypothesis 4, as there clearly is volatility spillover domination by a specific currency.

4.5 Cross-rate effects

As a complementary assessment we also considered cross-rate effects among the three new EU currencies. The BIS Triennial Forex Survey explicitly provides a guidance on their relative significance. BIS (2016, 2013) show that over-the-counter (OTC) daily exchange rate turnover among new EU currencies declined by 35 to 50 percent between 2013 and 2016 (Table A4). The decline in forex activity in the new EU forex market corresponds entirely with the overall decline in the total traded volume in global forex market along with decrease in cross-trade activity. Decline in forex trading volumes during 2013-2016 was linked with the weaker activity in Japanese yen (JPY) and stronger U.S. dollar (BIS, 2016; p.4). The expansionary monetary policy of the Bank of Japan prompted the demand for yens and increased trading activity in the yen cross rates in 2013; these trading incentive disappeared in 2016, though (BIS, 2016; p. 4).

The above global development sets the stage for smaller markets because similar trend can be observed in new EU currencies. Their traded volume was rising continuously from 1995 till 2013 when it reached the peak, as we present in Table A4. The ECB, analogically with the Bank of Japan, presented its first steps of the unconventional expansionary monetary program in the end of 2012. Polish, Hungarian and Czech central banks followed the steps of the ECB and implemented expansionary monetary policy by decreasing interest rates; in addition Czech National Bank launched forex interventions in November 2013. According to Rime and Schrimpf (2013; p.28), the rise in forex trading activity between 2010 and 2013 was mainly caused by the diversification of international asset portfolios. The new monetary environment made investors to rebalance their portfolios. As a consequence, trading activity jumped in the whole forex market including that with new EU currencies that provide investors with great diversification characteristics, especially during turbulent periods.

We show in the Section 4.2.3. and in the Figure 2 that conditional correlations between the new EU currencies and the USD/EUR decrease to negative territory during the GFC (2008-2010) and the EU debt crisis (2010-2012). Correlations are stable throughout the market distress and their negative values provide investors with diversification and hedging opportunities against the U.S. dollar. Antonakakis (2012) show that the most expensive hedging is between highly correlated currencies. With declining correlation, the cost of hedging decreases. We show in Section 4.3 and Table 3 that portfolio weights are stable during the post-debt crisis period; the exception is the Czech koruna after the Czech central bank launched forex interventions in late 2013. Currency interventions decrease the weight of the CZK in the portfolio and may have been the reason for decline in the cross-trade volume.

Despite substantial diversification benefits illustrated above, and in more detail in Section 4.3, Rime and Schrimpf (2013; p.28) show that currency carry-trades were unattractive under low yields in advanced economies during 2010-2013. Since carry-trade is a forex representation of the uncovered interest rate parity (UIRP), we also tested the UIRP among the three cross-rates (HUF/PLN, HUF/CZK, CZK/PLN) during the period after the EU debt crisis. We tested the UIRP with a standard specification:

$$(s_{t+1} - s_t)/s_t = \alpha + \beta(r_{1t} - r_{2t}) + \varepsilon_t\,, \tag{14}$$

where s_t is the spot forex cross-rate (HUF/PLN, HUF/CZK, CZK/PLN; units of domestic currency are in numerator; denominator represents 1 unit of foreign currency), r_{1t} and r_{2t} are the official interest rates at time t for domestic and foreign currencies, respectively. The null hypothesis $\alpha = 0$ and $\beta = 1$ tests the significance of the risk premium and the UIRP.

Coefficients present in Table A5 are statistically insignificant but the results suggest that the UIRP does not hold for cross-pairs involving the Czech koruna. Negative β indicates the failure of the UIRP in the CZK/PLN because $\beta < 0$ suggests profit from carry-trade by investing in the currency with higher interest rate followed by the appreciation of this currency. A forward premium puzzle in the Czech koruna can be detected due to the forex interventions of the Czech National Bank that protected the CZK from appreciation against euro from November 2013 till April 2017. The result is consistent with that of Vasilyev et al. (2017) who detected forward premium puzzle in advanced economies as well as in the Czech Republic. Further, HUF/CZK show insignificant parameter β with the value close to zero. Finally, the UIRP may be only identified in the HUF/PLN with β close to 2, and α approaching zero suggesting constant risk premium. However, these inferences must be presented with caution because both coefficients are statistically insignificant. Still, the finding is not uncommon as Lothian and Wu (2011) show that the UIRP does not hold over short time period and for small interest-rate differentials. Such setting corresponds to the currencies under research because after the EU debt crisis, the Polish, Hungarian and Czech central banks decreased their interest rates and the step resulted in very small interest rate differentials among the three currencies. Low interest rate environment naturally lowered attractiveness of the new EU currencies and resulted in lower traded volumes in 2016, as shown in Table A4.

Despite that the overall situation on financial markets after the EU debt crisis calmed down, volatility spillovers on the new EU forex markets increased again in 2017 due to geopolitical tensions (see Figure 3 and our detailed discussion in Section 4.4). Such development offers a direct implication for our analysis. Volatility represents a systematic risk that is considered a compelling factor for carry-trade operations. However, Menkhoff et al. (2012) show that profitability of the carry-trade strategy increases with decreasing volatility of the exchange rates. This is because a highly volatile environment creates error in exchange rate estimation and makes carry-trade less profitable. For that reason, during 2013-2016, we can also witness lower volumes of cross-trades realized in the three currency pairs (see Table A4 for details).

5. Conclusion

We analyze time-varying exchange rate comovements and volatility spillovers in the new EU forex market from 1999-2018. Specifically, we examine conditional correlations and volatility spillovers between the Czech, Hungarian, and Polish currencies with respect to the euro, and the dollar/euro exchange rate as a proxy for the world forex market. We show how the new EU forex market correlates with the U.S. dollar by employing the DCC model and the Diebold-Yilmaz spillover index as our key analytical tools. Our results document the evolution of currency interdependencies and volatility spillovers during calm and distressed 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 to pre-crisis levels. However, after the U.S. withdrew from the NAFTA agreement and the Fed started to tighten monetary conditions, the fear from global trade war increased and the correlations moved into the negative territory again. These outcomes conflict with the general understanding that correlations between financial assets increase during turbulent periods. On the contrary, we ask whether new EU currencies help investors diversify their portfolios during crisis periods. If yes, how much would that process cost? The results imply low correlations on the new EU forex markets during periods of distress that offer valuable diversification opportunities.

These potential portfolio benefits come at a price, 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, hedging is most costly during the GFC, and the cheapest hedging is observed in the period before the GFC. We show that portfolio diversification benefits offered by the new EU currencies may have been exploited by investors during the turbulent periods of the GFC and the EU debt crisis as witnessed by the increased volumes of cross-trades at those times.

In terms of volatility spillovers, we examine mutual volatility spillovers between new EU currencies together with spillovers between new EU currencies and the world forex market. 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. 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 and its actors in the EU. We document significant differences in the extent of currency comovements during various periods related to market distress. The extent of distress is further related to real economic and financial events. Moreover, low correlations reflect different patterns of behavior in the world forex market and in new EU currencies during crisis periods. These results imply favorable diversification benefits for the investors investing in the new EU currencies. Despite that comovements between new EU currencies and USD/EUR are similar in individually examined time periods, the hedge-ratio calculations show that it is worth to treat new EU currencies individually and not a as group. We show that all three currencies bring hedging benefits during crisis periods, but at different costs.

References

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

Aghion, P., Bacchetta, P., Rancière, R., Rogoffa, K. (2009). Exchange rate volatility and productivity growth: The role of financial development. Journal of Monetary Economics, 56(4), 494-513.

Ahmed, S., Zlate, A. (2014). Capital flows to emerging market economies: A brave new world? Journal of International Money and Finance, 48, Part B, 221-248.

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.

Andreou, E., Ghysels, E. (2009). Structural Breaks in Financial Time Series. Handbook of Financial Time Series. Springer, Berlin, Heidelberg.

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., Chen, J. (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.

Bai, J., Perron, P. (1998). Estimating and Testing Linear Models with Multiple Structural Changes. Econometrica, 66, 47–78.

Bai, J., Perron, P. (2003). Critical Values for Multiple Structural Change Tests. The Econometrics Journal, 6, 72–78.

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

Bank for International Settlements (BIS). (2013). Triennial Central Bank Survey Foreign exchange turnover in April 2013. Available online (https://www.bis.org/publ/rpfx13.htm).

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

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

Belke, A., Gros, D. (2002). Designing EU–US Atlantic monetary relations: exchange rate variability and labor 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.

Bohl, M.T., Branger, N., Trede, M. (2017). The case for herding is stronger than you think. Journal of Banking & Finance, 85, 30-40.

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.
Chowdhury, A.R., Wheeler, M. (2008). Does Real Exchange Rate Volatility Affect Foreign Direct Investment? Evidence from Four Developed Economies. The International Tradel Journal, 22(2), 218-245.
Chow, G.C. (1960). Tests of Equality Between Sets of Coefficients in Two Linear Regressions. Econometrica, 28(3),591-605.
Corsetti, G., Pericoli, M., Sbracia, M. (2005). Some contagion, some interdependence: More pitfalls in tests of financial contagion. Journal of International Money and Finance, 24(8), 1177-1199.
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., Garlappi, G., Uppal, R. (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.
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.
Fengler, M.R., Gisler, K.I. (2015). A variance spillover analysis without covariances: what do we miss? Journal of International Money and Finance, 51, 174-95.
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.
Garcia, R., Tsafack, G. (2011). Dependence structure and extreme comovements in international equity and bond markets. Journal of Banking and Finance, 35(8), 1954-1970.
Gilmore, C.G., McManus, G.M. (2002). International portfolio diversification: US and Central European equity markets. Emerging Markets Review, 3(1), 69-83.
Gray, D. (2014). Central European foreign exchange markets: a cross-spectral analysis of the 2007 financial crisis. The European Journal of Finance, 20(6), 550-567.
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.

Hau, H. (2002). Real Exchange Rate Volatility and Economic Openness: Theory and Evidence. Journal of Money, Credit, and Banking, 34(3), 611-630.

Jawadi, F., Ftiti, Z. (2017). Uncertainty and the United States' election effect on the economy: Some thoughts and empirical illustrations. Applied Economic Letters, 24(20), 1472-1475.

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.

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.

Longin, F., Solnik, B. (2001). Extreme correlations in international Equity Markets. Journal of Finance, 56(2), 649-676.

Lothian, J.R., Wu, L. (2011). Uncovered interest-rate parity over the past two centuries. Journal of International Money and Finance, 30, 448-473.

Markowitz, M.H. (1991). Foundations of portfolio theory. The Journal of Finance, 46(2), 469-77.

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.

Menkhoff, L. (2013). Foreign exchange intervention in emerging markets: a survey of empirical studies. World Economics, 36(9), 1187–1208.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A. (2012). Carry Trades and Global Foreign Exchange Volatility. The Journal of Finance, 67(2), 681–718.

Mensi, W., Hammoudeh, S., Shahzad, S.J.H., Shahbaz, M. (2017). Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. Journal of Banking & Finance, 75, 258-279.

Miyajima, K., Mohanty, M.S., Chan, T. (2015). Emerging market local currency bonds: Diversification and stability. Emerging Markets Review, 22(C), 126-139.

Pesaran. M.H., Pettenuzzo, D., Timmermann, A. (2006). Forecasting Time Series Subject to Multiple Structural Breaks. The Review of Economic Studies, 73(4), 1057–1084.

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.

Rime, D., Schrimpf, A. (2013). The anatomy of the global FX market through the lens of the 2013 Triennial Survey. BIS Quarterly Review, December 2013. Available online (https://www.bis.org/publ/qtrpdf/r_qt1312e.pdf).

Rodríguez, F.F., Puig, M.G., Rivero, S.S. (2015). Volatility spillovers in EMU sovereign bond markets. International Review of Economics and Finance, 39, 337-352.

Rose, A. (2000). One money, one market: the effect of common currencies on trade. Economic Policy, 30(April), 9–45.

Singh, P., Kumar, B., 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.

Tsuchiya, Y. (2015). Herding behavior and loss functions of exchange rate forecasters over interventions and financial crises. International Review of Economics & Finance, 39, 266-276.

Vasilyev, D., Busygin, V., Busygin, S. (2017). Testing and interpreting uncovered interest parity in Russia. Russian Journal of Economics, 3, 158–173.

Wu, G. (2001). The Determinants of Asymmetric Volatility. Review of Financial Studies, 14(3), 837-59.

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 May 31, 2018.

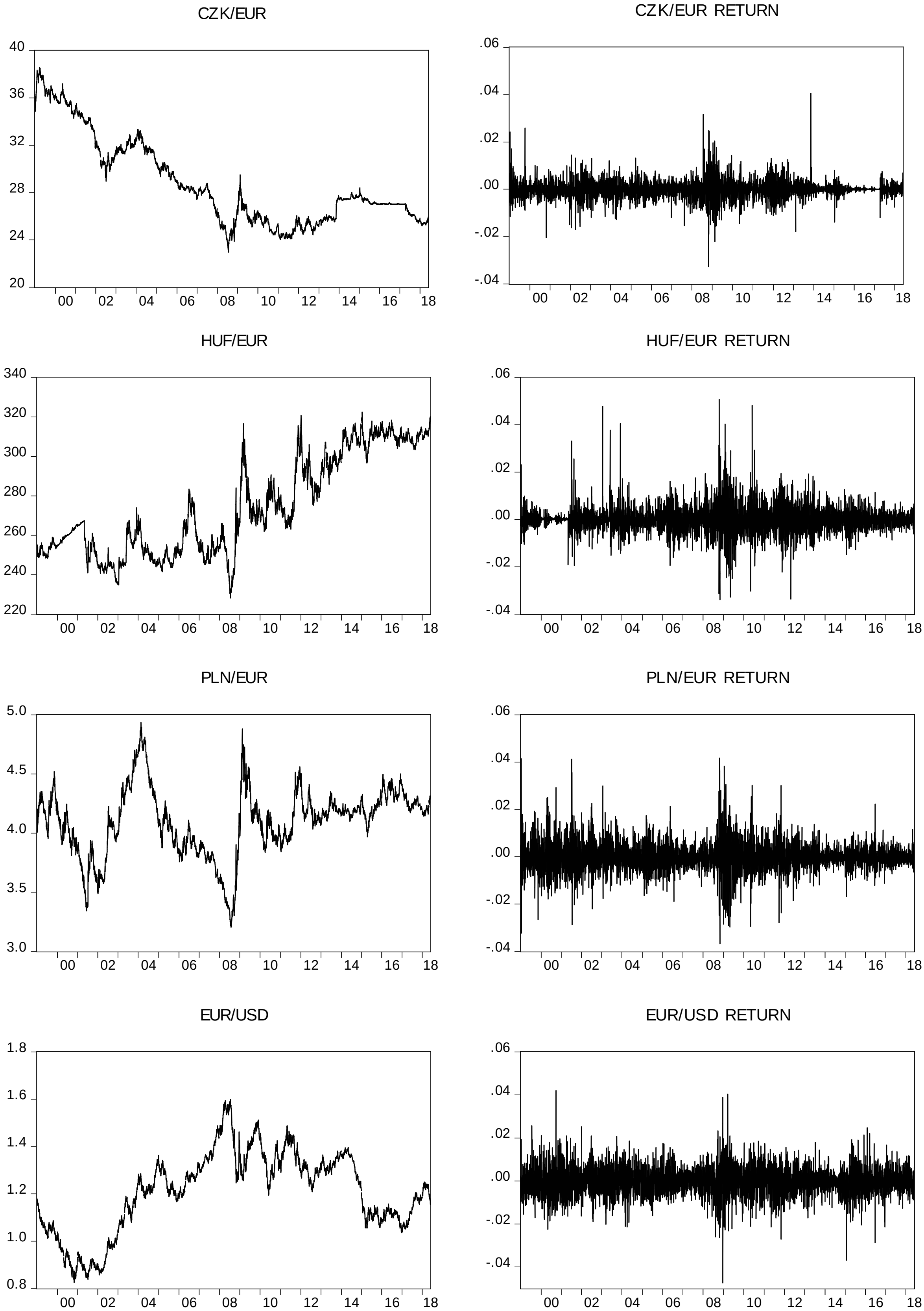
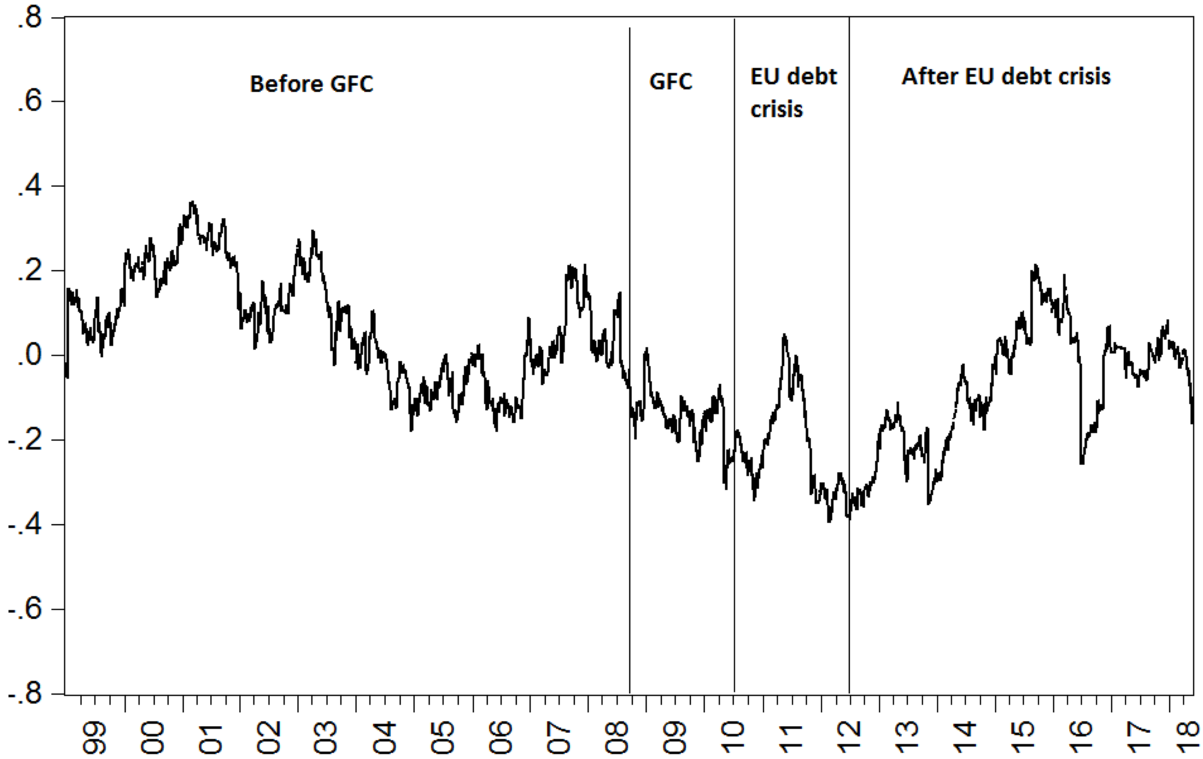


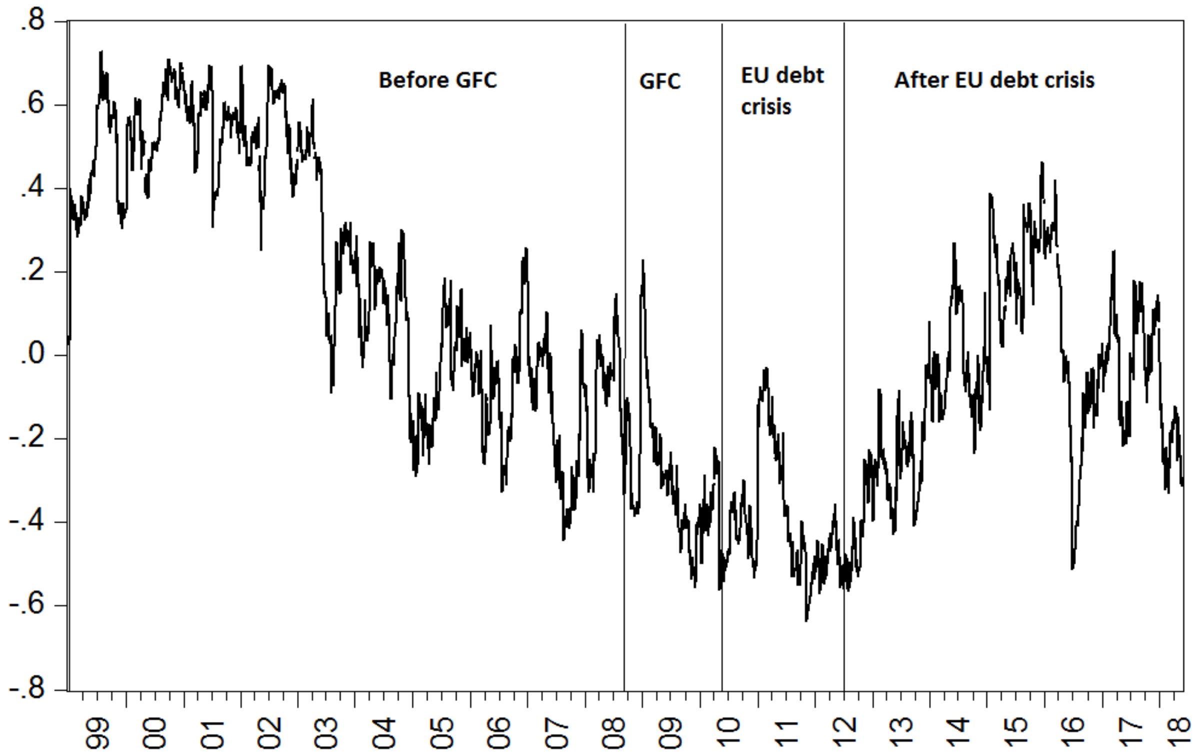
Figure 2

Dynamic conditional correlations.

A: CZK/EUR and USD/EUR in the period of 1999-May 2018.



B: PLN/EUR and USD/EUR in the period of 1999-May 2018.



C: HUF/EUR and USD/EUR in the period of 1999-May 2018.

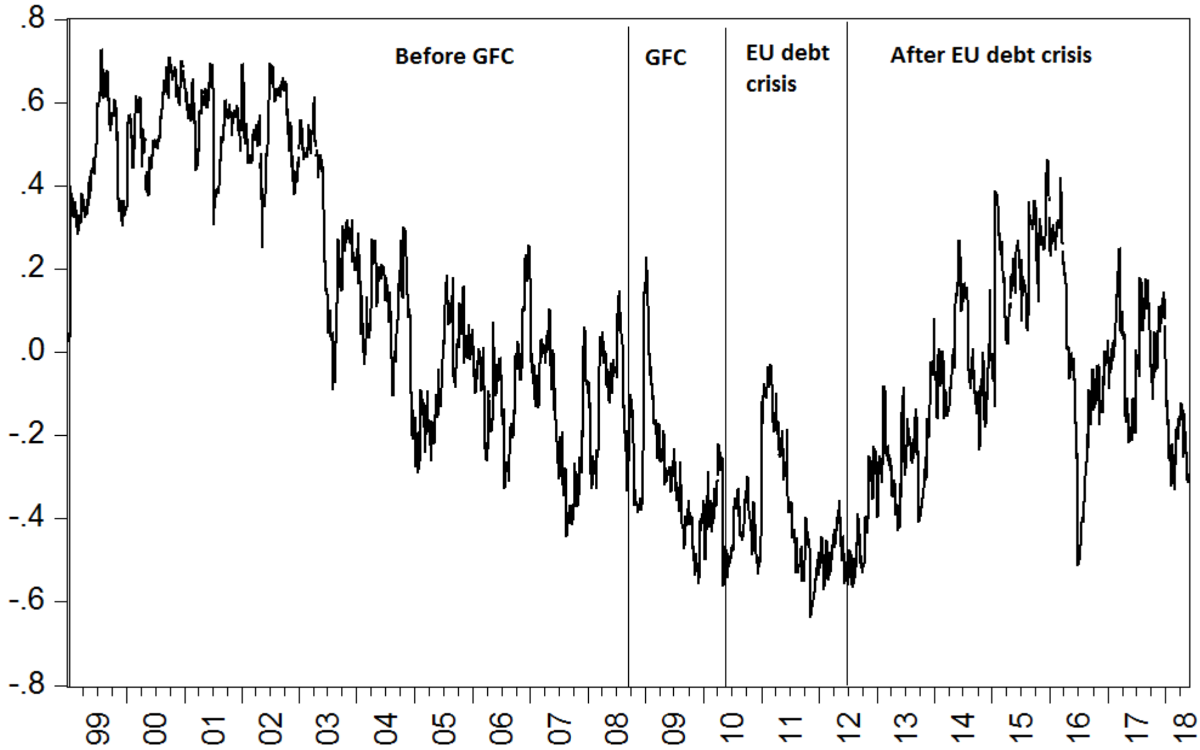


Figure 3: Total volatility spillovers in the period of 1999-May 2018.

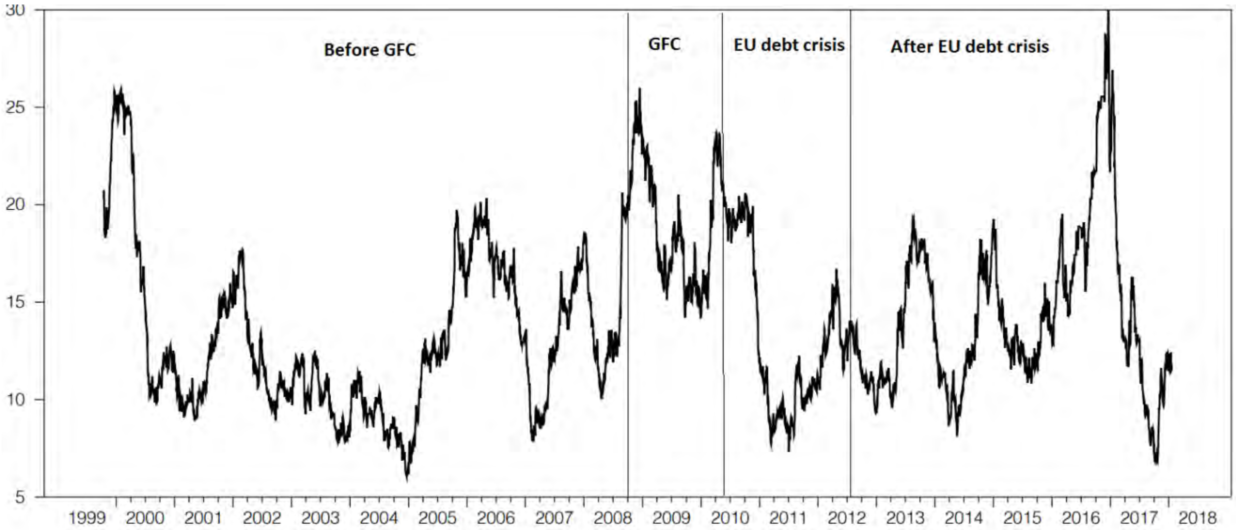
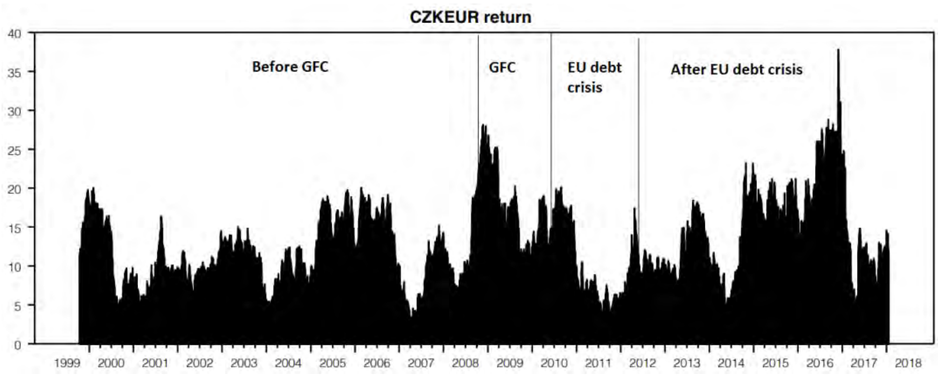
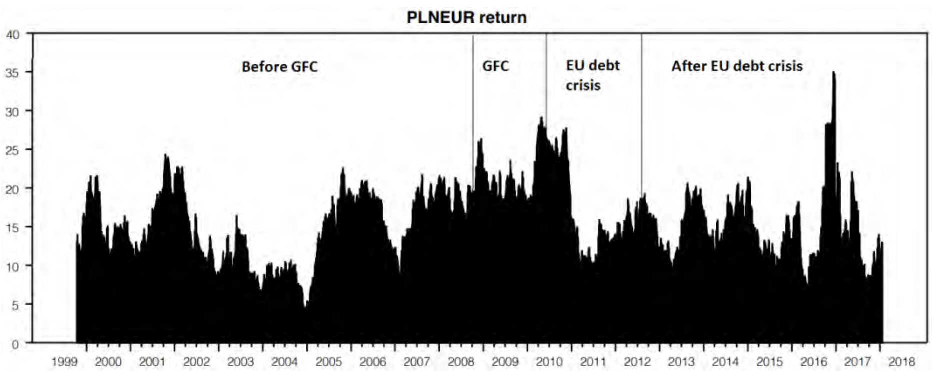


Figure 4: Directional volatility spillovers FROM 4 markets; 200-day rolling windows.

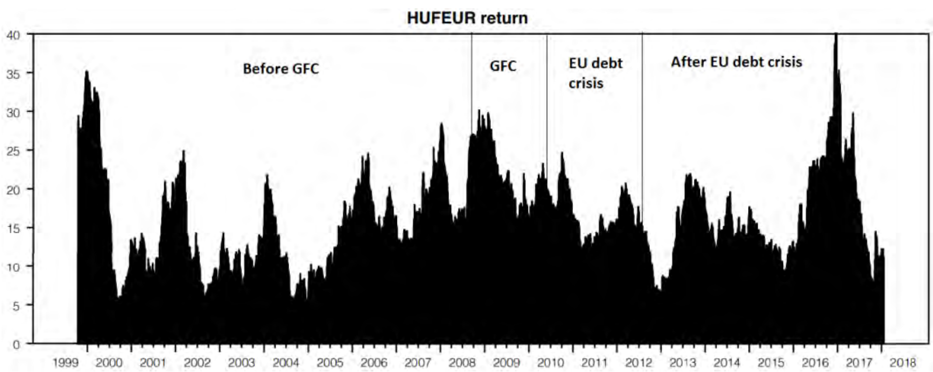
A: CZK/EUR



B: PLN/EUR



C: HUF/EUR



D: USD/EUR

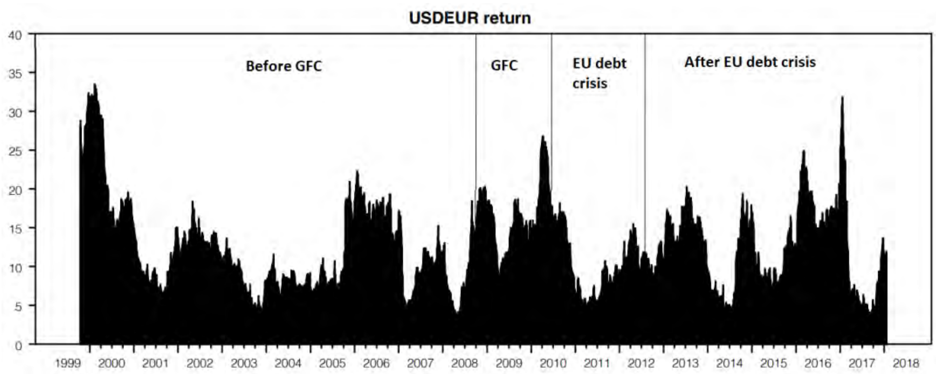
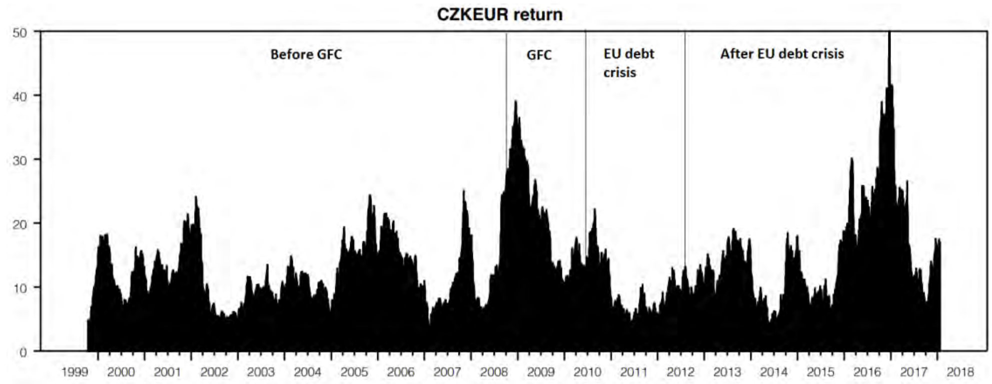
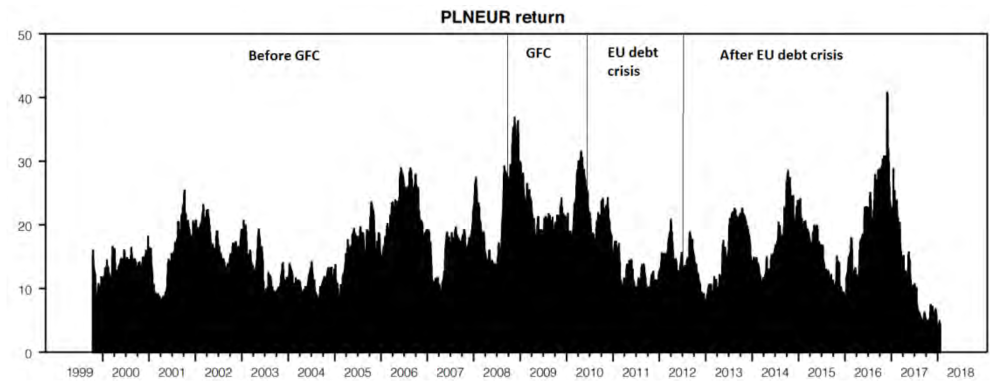


Figure 5: Directional volatility spillovers TO 4 markets; 200-day rolling windows.

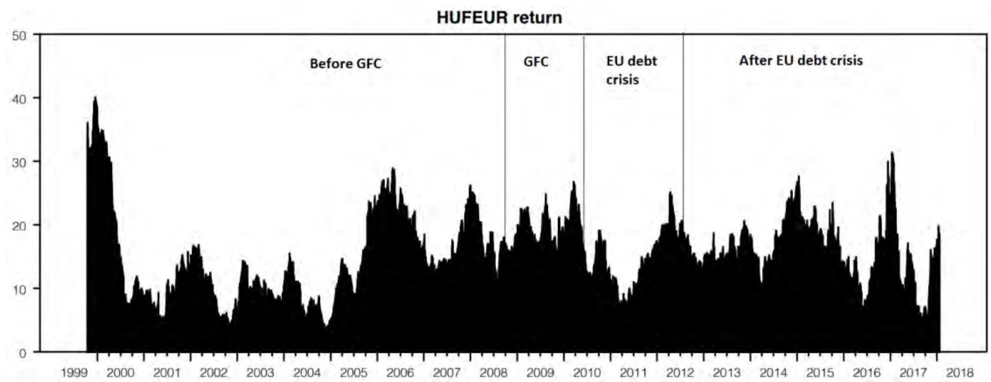
A: CZK/EUR



B: PLN/EUR



C: HUF/EUR



D: USD/EUR

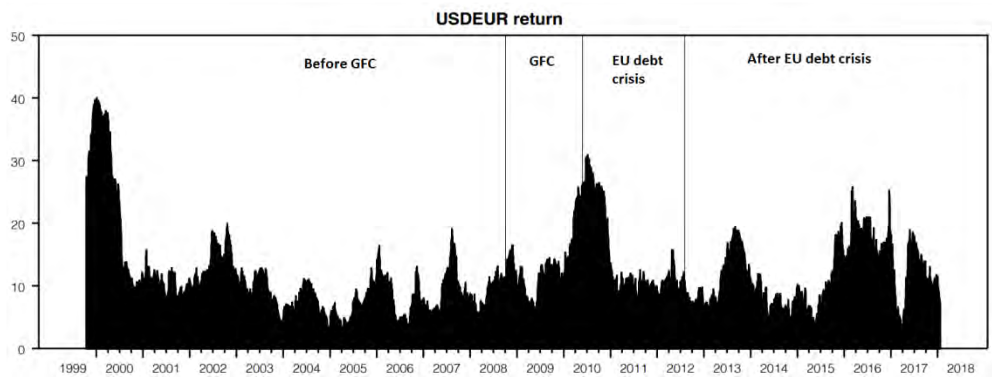
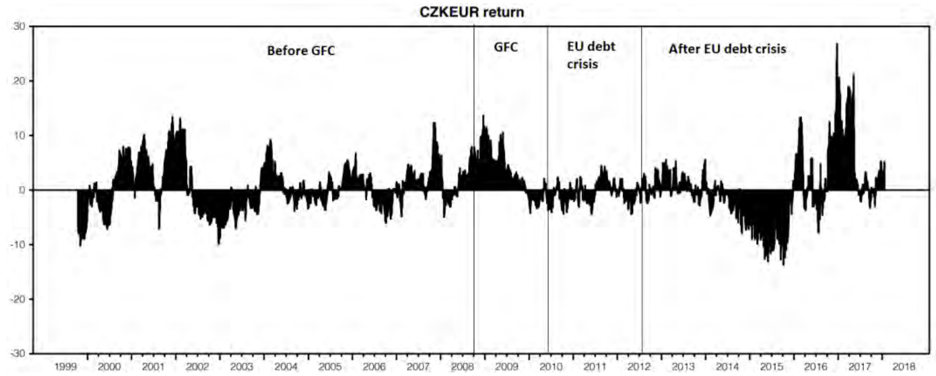
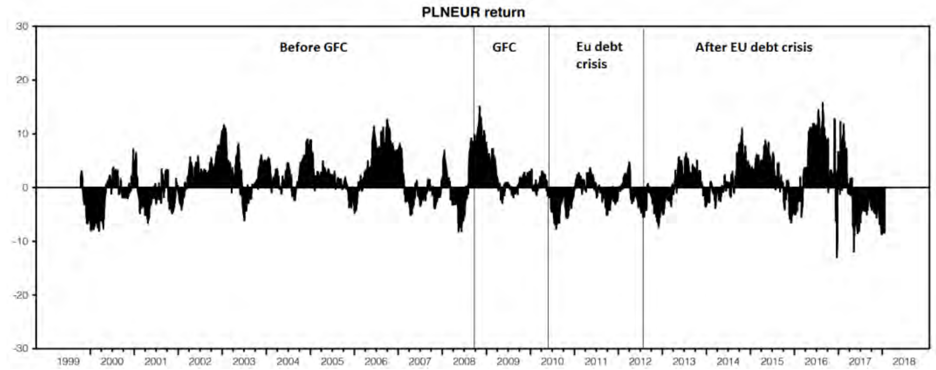


Figure 6: Net volatility spillovers; 4 markets; 200-day rolling windows.

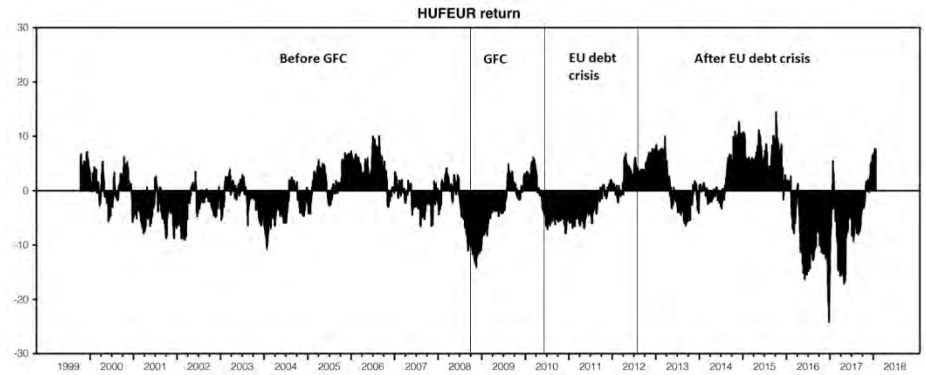
A: CZK/EUR



B: PLN/EUR



C: HUF/EUR



D: USD/EUR

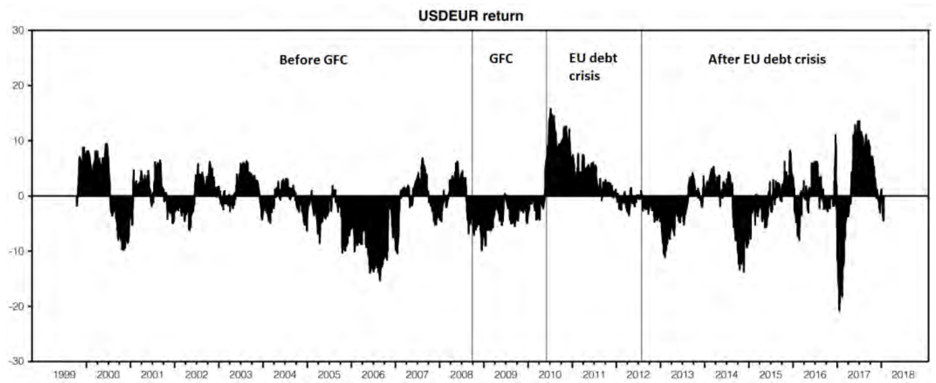


Table 1

Estimation results of the DCC model.

	Before GFC (1.1.1999-14.9.2008)			GFC crisis (15.9.2008 - 30.4.2010)			EU Debt crisis (3.5.2010-26.7.2012)			After EU debt crisis (27.7.2012-31.5.2018)		
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*	-0.0001	-0.0000
	(0.0022)	(0.0003)	(0.6092)	(0.6167)	(0.7167)	(0.5626)	(0.8984)	(0.5321)	(0.7445)	(0.0353)	(0.1440)	(0.5860)
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
	(0.0002)	(0.0002)	(0.0000)	(0.4352)	(0.3641)	(0.1719)	(0.1556)	(0.0292)	(0.0331)		(0.0029)	(0.1163)
α	0.0699**	0.0885**	0.0488**	0.0883**	0.0736**	0.1167**	0.0680**	0.0412*	0.0312*	0.1677**	0.1276**	0.0317**
	(0.0000)	(0.0000)	(0.0000)	(0.0013)	(0.0016)	(0.0002)	(0.0071)	(0.0345)	(0.0213)	(0.0000)	(0.0000)	(0.0001)
β	0.9029**	0.8945**	0.9486**	0.9042**	0.9185**	0.8762**	0.9174**	0.9189**	0.9515**	0.7901**	0.8373**	0.9637**
	(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 param.	1.2184**	1.4001**	1.5000**	1.5488**	1.5233**	1.4561**	1.3821**	1.4235	1.5344**	1.1257**	1.4022**	1.5304**
	(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	22.2180	25.2990	23.6220
	(0.9970)	(0.1220)	(0.9820)	(0.1450)	(0.6940)	(0.9280)	(0.8060)	(0.5490)	(0.6630)	(0.8460)	(0.7100)	(0.7890)
$Q^2(30)$	15.1510	29.0830	0.7264	20.7560	22.2590	17.6920	22.9460	36.8240	14.2490	3.6778	18.8010	33.437
	(0.9890)	(0.5130)	(1.0000)	(0.8950)	(0.8440)	(0.9630)	(0.8170)	(0.1820)	(0.9930)	(1.0000)	(0.9440)	(0.3040)
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	-0.0721	-0.0601	-0.1107
α	0.0076**	0.0287**	0.0413**	0.0307	0.1091**	0.0714*	0.0206*	0.0331*	0.0132	0.0099**	0.0186**	0.0188**
	(0.0010)	(0.0000)	(0.0000)	(0.3861)	(0.0015)	(0.0414)	(0.0172)	(0.0301)	(0.6084)	(0.0026)	(0.0000)	(0.0001)
β	0.9905**	0.9651**	0.9552**	0.7300	0.7110**	0.8087**	0.9657**	0.8962**	0.7864	0.9784	0.9703	0.9704
	(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	9.6228	18.7375	22.5271

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. The AR(1)-GARCH (1,1) model is employed if the serial correlation in the residuals of GARCH(1,1) model is presented. 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	4.7487	0.0000
PLN/EUR & USD/EUR	9.4709	0.0000
HUF/EUR & USD/EUR	8.6962	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 - 14.9.2008)					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	0.5610	0.0818	0.2702	0.8342
CZK/HUF	0.2325	0.1618	-0.2863	0.6677	CZK/HUF	0.5809	0.0399	0.4565	0.6741
PLN/HUF	0.4370	0.1733	-0.0229	0.8656	PLN/HUF	0.7158	0.0644	0.5288	0.8593
Portfolio weights (currency i/currency j)					*Portfolio weights (currency i/currency j)*				
CZK/PLN	0.5055	0.1524	0.0612	1.0866	CZK/PLN	0.5002	0.0906	0.1681	0.7800
CZK/HUF	0.5349	0.1981	0.1524	0.9842	CZK/HUF	0.4962	0.0529	0.3743	0.6897
PLN/HUF	0.5673	0.1981	0.1291	1.1216	PLN/HUF	0.4914	0.0868	0.2478	0.7425
EU debt crisis (3.5.2010 - 26.7.2012)					**After EU debt crisis (27.7.2012 - 31.05.2018)**				
Hedge ratio (long/short)					*Hedge ratio (long/short)*				
	Mean	Std. dev.	Min	Max		Mean	Std. dev.	Min	Max
CZK/PLN	0.4298	0.1009	0.2254	0.6513	CZK/PLN	0.3175	0.1533	-0.0088	0.8333
CZK/HUF	0.4188	0.0531	0.3065	0.5125	CZK/HUF	0.1932	0.1241	-0.1514	0.5884
PLN/HUF	0.6355	0.0780	0.3724	0.8731	PLN/HUF	0.4967	0.1434	0.1266	0.8306
Portfolio weights (currency i/currency j)					*Portfolio weights (currency i/currency j)*				
CZK/PLN	0.5001	0.0461	0.3944	0.6526	CZK/PLN	0.3897	0.1324	0.1084	0.8102
CZK/HUF	0.5010	0.0263	0.4474	0.5997	CZK/HUF	0.3972	0.1089	0.1641	0.7718
PLN/HUF	0.4968	0.1066	0.1026	1.0434	PLN/HUF	0.5243	0.0995	0.2449	0.7844

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	95.94	1.70	1.61	0.75	4.10
PLN/EUR	0.99	94.01	3.97	1.04	6.00
HUF/EUR	2.36	3.75	93.42	0.47	6.60
USD/EUR	1.08	0.71	0.72	97.50	2.50
Contribution to others	4.40	6.20	6.30	2.30	**Index:**
Contribution including own	100.40	100.20	99.70	99.80	4.80%
Net Spillover	0.40	0.20	-0.30	-0.20	

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.

Appendix

Table A1

Descriptive statistics of the examined exchange returns.

	Before GFC (1.1.1999 - 14.9.2008)				GFC (15.9.2008-30.4.2010)				EU debt crisis (3.5.2010-26.7.2012)				After EU debt crisis (27.7.2012-31.05.2018)			
	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	1494	1494	1494	1494
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	0.0000	0.0000	0.0001	0.0000
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	0.0022	0.0035	0.0039	0.0052
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	3.8633	0.1989	0.1826	-0.2534
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	85.57	5.44	4.92	6.77
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***	-38.73***	-38.61***	-39.58***	-39.70***
JB	4984.14***	2201.64***	18633***	261.19***	122.52***	74.24***	164.89***	201.33***	28.55***	340.01***	497.89***	8.31**	427884***	381.18***	236.72***	898.18***
	[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	8.54	2.66	20.605**	8.17
	[0.711]	[0.012]	[0.048]	[0.567]	[0.423]	[0.023]	[0.377]	[0.067]	[0.057]	[0.079]	[0.383]	[0.893]	[0.576]	[0.988]	[0.024]	[0.613]
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	6.057	176.89***	272.22***	13.987
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.628]	[0.132]	[0.810]	[0.000]	[0.000]	[0.174]
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	0.26	13.85***	22.94***	2.07*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.444]	[0.335]	[0.933]	[0.000]	[0.000]	[0.067]

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 10%, 5% and 1% levels, respectively.

Table A2

Structural breaks: Estimated results for the Chow test with single structural change

	Chow test								
	Break date	**F-statistics**	**Prob. F**	**Break date**	**F-statistics**	**Prob. F**	**Break date**	**F-statistics**	**Prob. F**
USD/EUR	**14.9.2008**	24.22	0.00***	**30.4.2010**	222.59	0.00***	**26.7.2012**	499.31	0.00***
CZK/EUR	**14.9.2008**	5.52	0.02**	**30.4.2010**	297.48	0.00***	**26.7.2012**	418.07	0.00***
PLN/EUR	**14.9.2008**	3.15	0.08*	**30.4.2010**	449.14	0.00***	**26.7.2012**	593.06	0.00***
HUF/EUR	**14.9.2008**	325.16	0.00***	**30.4.2010**	24.71	0.00***	**26.7.2012**	297.07	0.00***

Notes: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A3

Test of changes in dynamic correlations among the new EU exchanges rates and USD/EUR during the examined time period (1.1.1999 – 31.05.2018)

	CZK/EUR - USD/EUR		**PLN/EUR - USD/EUR**		**HUF/EUR - USD/EUR**	
P_{t-1}	1.019	0.00***	1.014	0.00***	0.986	0.00***
P_{t-2}	-0.027	0.06*	-0.023	0.10*		
$DM_{1,t}$	-0.002	0.06*	-0.004	0.05**	-0.005	0.02**
$DM_{2,t}$	-0.003	0.00***	-0.006	0.00***	-0.007	0.00***
$DM_{3,t}$	-0.001	0.07*	0.002	0.08*	-0.002	0.13
Q(5)	5.570		0.920		3.810	
ARCH(5)	0.990		0.990		0.990	

Notes: $DM_{1,t}$ stands for the GFC (15.9.2008 – 30.4.2010), $DM_{2,t}$ is the dummy variable for the EU debt crisis (3.5.2010 – 26.7.2012), dummy $DM_{3,t}$ represents the period after the EU debt crisis (27.7.2012 – 31.05.2018). The lag length is chosen by AIC criterion. Serial correlation in the residuals is tested by the Ljung-Box Q-statistics up to five lags Q(5), heteroscedasticity in the residuals is tested by the ARCH LM test up to five lags ARCH(5). *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table A4

Turnover of the OTC foreign exchange instruments by currency

	1995	1998	2001	2004	2007	2010	2013	2016
USD [a]	981	1325	1114	1702	2845	3371	4662	4438
EUR [a]			470	724	1231	1551	1790	1591
HUF [a]		1	0.1	4	9	17	23	15
CZK [a]		4	2	3	7	8	19	14
PLN [a]		1	6	7	25	32	38	35
Total FX Market [a]	1182	1527	1239	1934	3324	3973	5357	5057
PLN/CZK [b]							173	115
PLN/HUF [b]							68	44
HUF/CZK [b]							63	36
HUF/PLN [b]							162	65

Note: a) Turnover of the OTC foreign exchange instruments, by currency "Net-net" basis; April 1995-2016 daily averages, in billions of US dollars. Source: https://stats.bis.org/statx/srs/table/d11.3, b) OTC foreign exchange turnover "net-gross" basis; daily averages, in millions of US dollars, specified currency against all other currencies. Source: BIS (2016, 2013). These data are not available in the BIS Triennial reports published before 2013.

Table A5

Uncovered interest rate parity regressions on the new EU cross-rates for the period after the EU debt crisis (27.7.2012 - 31.05.2018)

	α	Prob.	β	Prob.	R^2
HUF/PLN	0.001	0.639	2.062	0.477	0.007
CZK/PLN	-0.003	0.463	-1.781	0.461	0.008
HUF/CZK	0.001	0.674	0.158	0.907	0.002

Figure A1

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