Volatility Transmission in Emerging European Foreign Exchange Markets

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Abstract

This paper studies the dynamics of volatility transmission between Central European currencies and euro/dollar foreign exchange using model-free estimates of daily exchange rate volatility based on intraday data. We formulate a flexible yet parsimonious parametric model in which the daily realized volatility of a given exchange rate depends both on its own lags as well as on the lagged realized volatilities of the other exchange rates. We find evidence of statistically significant intra-regional volatility spillovers among the Central European foreign exchange markets. With the exception of the Czech currency, we find no significant spillovers running from euro/dollar to the Central European foreign exchange markets. To measure the overall magnitude and evolution of volatility transmission over time, we construct a dynamic version of the Diebold-Yilmaz volatility spillover index, and show that volatility spillovers tend to increase in periods characterized by market uncertainty.

JEL-Code: C50, F31, G15.

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1. Introduction

The financial and economic turbulence during 2008–2009 renewed interest in understanding the nature of information transmission on and among financial markets (Dooley & Hutchinson, 2009). Recent economic crises have often included large and unexpected movements in the prices of various financial instruments, including foreign exchange rates (Melvin & Taylor, 2009) (Muller & Verschoor, 2009). These movements are a direct symptom of a pervasive uncertainty that transcended the boundaries of individual markets (Bartram & Bodnar, 2009), not excluding emerging markets in Europe. On the contrary, these European markets felt the impact of the recent crisis, and were in no way isolated from it (Dooley & Hutchinson, 2009). Motivated by the impact of the recent crisis, this study analyzes the dynamics of volatility transmission to, from and among Central European (CE) foreign exchange markets. In particular, we analyze volatility spillovers among the Czech, Hungarian and Polish currencies together with the U.S. dollar during the period 2003–2009, and the extent to which shocks to foreign exchange volatility in one market transmit to current and future volatility in other currencies.

Despite their growing integration with developed markets, in terms of volatility transmission, European emerging markets are under-researched. The joint behavior of the volatility of Central European currencies is of key importance for international investors contemplating the diversification benefits of allocating part of their portfolio to Central European assets. In fact, according to (Jotikasthira, Lundblad, & Ramadorai, 2009), developed-country-domiciled mutual and hedge fund holdings already account for about 14–19% of the free-float adjusted market capitalization in Central Europe (17.7% in the Czech, 18.25% in the Hungarian and 14.55% in the Polish equity markets). Since international stock market co-movements tend to be stronger in periods of distress and therefore high volatility (King & Wadhwani, 1990), an increase in foreign exchange volatility further amplifies the variability of internationally allocated portfolios for investors whose consumption is denominated in a developed-country currency. The associated rise in the cost of hedging foreign exchange risk then plays an important role in the investment decision-making process and requires a good understanding of the underlying foreign exchange volatility. The importance of volatility in the construction of portfolios in the CE foreign exchange markets is also shown in (de Zwart, Markwat, Swinkels, & van Dijk, 2009).

Further, there are even more fundamental reasons to be interested in analyzing the volatility transmission in European emerging markets, specifically the countries that joined the European Union in 2004. The new EU members committed themselves to adopting the euro upon satisfying a set of convergence criteria (the Maastricht criteria) defined for the Economic and Monetary Union (EMU). Foreign exchange volatility or foreign exchange risk can be interpreted as a measure of currency stability, which is an important precondition for preparing to adopt the euro. The precondition is to some extent in contrast with historical evidence that foreign exchange risk is pronounced in new EU members (Orlowski, 2005), (Kočenda & Valachy, 2006), (Fidrmuc & Horváth, 2008). The common source of this risk is the questionable perspective of the monetary and especially fiscal policies in new EU members (Kočenda, Kutan, & Yigit, 2008). Moreover, (Fidrmuc & Horváth, 2008) show that the low credibility of exchange rate management implies a higher volatility of exchange rates in new EU countries, and the volatility exhibits significant asymmetric effects. Finally, both real and nominal macroeconomic factors play important roles in explaining the variability of and contribute to the foreign exchange risk in the set of countries studied in this paper (Kočenda & Poghosyan, 2009). As these countries are in the process of coping with the Maastricht criteria to qualify for euro (EUR) adoption, identifying patterns of volatility transmission requires a detailed analysis.

The contribution of our paper to the existing literature is a thorough study of volatility transmission among Central European exchange rates and the U.S. dollar using high-frequency data. By relying on model-free non-parametric measures of ex-post volatility, our analysis is in sharp contrast to the existing empirical literature on CE exchange rates that employs almost exclusively a GARCH framework to study the dynamics of exchange rate volatility. We propose a simple and flexible multivariate time-series specification for the series of realized volatilities of the four exchange rates, allowing explicitly for the time-varying nature of the volatility of realized volatility itself. The model is essentially a multivariate generalization of the HAR-GARCH model of (Corsi, Mittnik, Pigorsch, & Pigorsch, 2008). Within the model we formally test for volatility spillovers by running simple pairwise Granger causality tests. To properly assess the overall magnitude and evolution over time of the volatility spillovers we construct a dynamic version of the Diebold-Yilmaz spillover index.

The onset of the sub-prime crisis of 2008 brought about a substantial change in the behavior of the exchange rates under research. Recursive estimation of our model indicates that a structural break occurred around the beginning of 2008 and was characterized by a dramatic increase of the level of exchange rate volatility as well as the volatility or realized volatility. We therefore split the sample into two parts, 2003–2007 and 2008–2009, and analyze the volatility spillovers by fitting our model separately for each sub-sample.

Our empirical results document the existence of volatility spillovers between the Central European foreign exchange markets. We find that each Central European currency is characterized by a different volatility transmission pattern. For example, during the pre-2008 period, volatilities of both the Czech koruna (CZK) and Polish zloty (PLN) were affected by both the short-term and the long-term volatility components of the Hungarian forint (HUF) as well as by the long-term volatility component of the U.S. dollar (USD). In contrast, the volatility of EUR/HUF seems irresponsive to any foreign component other than the medium-term volatility component of EUR/CZK. Furthermore, the Hungarian forint is also the only Central European currency that is not significantly affected by the volatility of EUR/USD.

The picture changes quite dramatically when we look at the crisis period of 2008–2009. While the pairwise Granger causality indicates virtually no spillovers, with the exception of the U.S. dollar Granger-causing the Czech koruna, the level of the Diebold-Yilmaz index increases substantially with respect to the pre-2008 period. This is due to the increased *contemporaneous* dependence of the realized volatility innovations. Thus, we find that in periods characterized by increased market uncertainty, the Central European exchange rates and U.S. dollar volatilities co-move more closely, which has important implications for the stability of the region as a whole.

The rest of the study is organized as follows. In Section 2, we provide a brief review of the literature on volatility transmission focusing primarily on the contributions that are most relevant for our work. In Section 3, we set out our theoretical framework and our modeling strategy pursued in the empirical part of the paper. Section 3 also includes the derivation of the dynamic version of the volatility spillover index. We describe the data in Section 4 and report the empirical results in Section 5. Section 6 concludes the paper with a short discussion and suggestions for future research.

2. Related Literature

The literature on volatility transmission is by no means extensive and certainly not as large as that on cross-market linkages in general (Claessens & Forbes, 2001). Three strands of literature emerge based on whether foreign exchange, equity or cross-market volatility transmission is investigated. Further division can be made based on whether low frequency (daily/weekly) or high-frequency (intraday) data is analyzed.

The studies of volatility transmission using daily and weekly data represent by far the largest part of the literature on the subject. This is especially true for the case of the volatility transmission across equity markets that includes, among others, the studies of (Engle, Ito, & Lin, 1990), (King & Wadhwani, 1990), (King, Sentana, & Wadhwani, 1994), (Lin, Engle, & Ito, 1994), (Susmel & Engle, 1994), (Karolyi, 1995), (Koutmos & Booth, 1995), (Kanas, 1998), (Ng, 2000) and (Corradi, Distaso, & Fernandes, 2009). Similarly to the analysis of other financial markets, the majority of the studies in this group employ a parametric framework to analyze the behavior of conditional variances and covariances (e.g. GARCH). The parametric approach is sometimes augmented with a Markov switching methodology to account for different volatility states (see e.g. (Engle & Sheppard, 2001), and (Gallo & Otranto, 2007)). A more detailed review of these studies is presented in (Soriano & Climent, 2006).

Studies of volatility transmission based on low-frequency Forex data are relatively sparse. (Bollerslev, 1990) uses a model with time-varying conditional variances and covariances, but constant conditional correlations, to model a set of five nominal European-U.S. dollar exchange rates in the period before and after the inception of the European Monetary System (EMS).

(Kearney & Patton, 2000) employ a series of multivariate GARCH models to analyze the volatility transmission between the members of the EMS prior to their complete monetary unification. (Kearney & Patton, 2000) provides many interesting findings on the exchange rate volatility transmissions within the EMS including the effect of time-aggregation on volatility transmission. In fact, less volatile weekly data is found to exhibit a significantly smaller tendency to transmit volatility compared to the more volatile daily data. This finding is consistent with the fact that markets have a greater propensity to transmit volatility in active as opposed to tranquil periods, as shown by (Andersen & Bollerslev, 1998) (Andersen & Bollerslev, 1998).

A different approach is pursued by (Hong, 2001) who studies the existence of Granger-causalities between two weekly nominal U.S. dollar exchange rates with respect to (the former) Deutsche mark (DEM) and Japanese Yen (JPY). His findings suggest that there exists only simultaneous interaction between the two exchange rates when it comes to causality in the mean and both simultaneous and one-way (DEM → JPY) interactions regarding the causality in the variance.

(Hong, 2001) belongs to a strand of literature that develops formal testing tools for causality in variance using low-frequency data. Following the seminal paper by (King & Wadhwani, 1990), (Hong, 2001) and the earlier study (Cheung & Ng, 1996) both work within the parametric framework anchored in specific formulations of the spillover effects to develop the tests based on the residual cross-correlation function. (van Dijk, Osborn, & Sensier, 2005) extend this analysis to account for the presence of structural breaks in volatility. Finally, (Diebold & Yilmaz, 2009) employ a vector autoregressive model as a basis for the variance decomposition of forecast error variances in order to measure the magnitude of return and volatility spillovers.

Although much can be learned from the analysis of daily or weekly data, this relatively low-frequency data may fail to detect both the effect of information that is incorporated very quickly as well as any short-run dynamic effects (Wongswan, 2006). Indeed, the findings of (Kearney & Patton, 2000) showed that a similar problem arises even at daily vs. weekly time horizons. A limited number of studies have recently appeared that make use of intraday or high-frequency data, hoping to address these and related issues. (Baillie & Bolerslev, 1991) examined volatility spillover effects as part of their study of four foreign exchange spot rates (GBP, JPY, DEM, and CHF) vs. USD, recorded on an hourly basis, for a six-month period in 1986. The authors failed to uncover the presence of volatility spillover effects between the currencies or across markets. (Engle, Gallo, & Velucchi, 2009) study daily (range) volatility spillovers based on a daily high-low range as a proxy for volatility. In contrast to many other studies, the authors employ the multiplicative error model (MEM) of (Engle R. F., 2002) to capture the dynamic relationships among volatilities (measured as daily range) in different markets. Finally, (Wongswan, 2006) makes use of high-frequency data to study the international transmission of fundamental economic information from developed economies (United States, Japan) to emerging economies (Korea, Thailand).

An important benefit of using high-frequency data is the improved estimation of low-frequency volatility and, consequently, an improved inference about volatility transmission. To the best of our knowledge there are only two studies that that make use of high-frequency data to construct realized measures of integrated variance as means of analyzing volatility spillovers in foreign exchange markets. (Melvin & Melvin, 2003) provide evidence of statistically significant intra- and inter-regional volatility spillovers in the DEM/USD and JPY/USD FX markets, given the theoretical settings offered by the heat wave and meteor-shower effects (Engle, Ito, & Lin, 1990). In a more recent study, (Cai, Howorka, &

Wongswan, 2008) study the transmission of volatility and trading activity across three major trading centers (Tokyo, London and New York) and two currency pairs (EUR/USD and USD/JPY) using minute-by-minute FX mid-quotes. Our work directly contributes to this literature by studying the Central European region.

3. Methodology

Following the approach of (Andersen, Bollerslev, & Diebold, 2007) we assume that the vector of the logarithmic spot exchange rate, $\boldsymbol{x}_t$, belongs to the class of jump-diffusions

$$\boldsymbol{x}_t = \boldsymbol{x}_0 + \int_0^t \boldsymbol{\mu}_u \mathrm{d}u + \int_0^t \boldsymbol{\Theta}_u \mathrm{d}\boldsymbol{w}_u + \boldsymbol{l}_t,$$

where $\boldsymbol{\mu}_t$ denotes a vector drift process, $\boldsymbol{\Theta}_t$ is the spot co-volatility process, $\boldsymbol{w}_t$ is a standard vector Brownian motion and $\boldsymbol{l}_t$ a vector pure-jump process of finite activity (i.e. the associated Levy density is bounded in the neighbourhood of zero). No parametric assumptions will be made regarding their respective laws of motion (Andersen T. G., Bollerslev, Diebold, & Labys, 2003).

A natural measure of variability in this model is the well-known quadratic variation as in (Protter, 2005) given by

$$\boldsymbol{QV}_t = \int_0^t \boldsymbol{\Theta}_u^{'} \boldsymbol{\Theta}_u \mathrm{d}u + \sum_{s\,\in[0,t]} \Delta\boldsymbol{l}_s^{'} \Delta\boldsymbol{l}_s,$$

where the first component captures the contribution of the diffusion, while the second component is due to jumps. To measure the daily quadratic variation of the individual components of $\boldsymbol{x}_t$ using intraday data we employ the realized variance (RV) defined as

$$RV_{i,t,M} = \sum_{i=1}^{M} \Delta_i x_{j,t}^2, \tag{1}$$

where $\Delta_i x_{j,t}$ denotes the i-th intraday return of the j-th components of $\boldsymbol{x}_t$ on day t. When we construct the realized variance estimator we have to account for the presence of market microstructure noise that renders the realized variance estimator in equation (1) biased and inconsistent. To this end, we employ the moving-average based estimator of (Hansen, Large, & Lunde, 2008).

Given the time series of realized volatilities, we employ a multivariate version of the heterogeneous autoregressive (HAR) model of (Corsi, 2009) to model their joint behavior. To formally define the multivariate HAR model, we stack the logarithmic realized variances of a set of assets into a vector $\boldsymbol{v}_t$**.** Working with logarithmic realized variance instead of realized variance itself has two advantages. First, no parameter restrictions are required to ensure the non-negativity of the realized variance and second, the distribution of the logarithmic realized variance is much closer to normality, which is attractive from a statistical point of view. The vector HAR (VHAR) specification is given by

$$\boldsymbol{v}_t = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 \boldsymbol{v}_{t-1} + \boldsymbol{\beta}_5 \boldsymbol{v}_{t-1|t-5} + \boldsymbol{\beta}_{22} \boldsymbol{v}_{t-1|t-22} + \boldsymbol{\gamma} \boldsymbol{z}_t + \boldsymbol{\varepsilon}_t,$$

where the $\boldsymbol{\beta}$'s are square matrices of coefficients, $\boldsymbol{z}_t$ is a vector of (exogenous) regressors, $\boldsymbol{\varepsilon}_t$ is a vector innovation term and the lagged vector of realized variances is

$$\boldsymbol{v}_{t-1|t-k} = \frac{1}{k} \sum_{j=1}^{k} \boldsymbol{v}_{t-j.}$$

Note that the model consists of three volatility components: daily, weekly and monthly, corresponding, in turn, to the first lag of the logarithmic realized variance and the normalized sums of the (previous) five-day and twenty-two-day logarithmic realized variance, respectively. These are meant to reflect the different reaction times of various market participants to the arrival of news. At the same time, they give the model an intuitive interpretation as they allow one to relate the volatility patterns over longer intervals to those over shorter intervals. This is highly relevant, for example, in the case of short-term market participants who may use the information contained in long-term volatility to adjust their trading behavior, thereby causing the volatility to increase in the short-term (Corsi, 2009).

The ability of the HAR model to describe the interaction(s) of volatility across time makes it an attractive tool for studying the volatility dynamics both within and across the exchange rates. Specifically, the HAR model allows analyzing how the long-term volatility affects the expectations about the future market trends and risk. Indeed, given the multivariate framework, we can study both the qualitative and quantitative implications of short-term and/or long-term volatility components characterizing one foreign exchange market on the evolution of another. Despite its simplicity, the HAR model has been shown to perform remarkably well in reproducing the widely documented presence of volatility of financial products; see e.g. (Andersen, Bollerslev, & Diebold, 2007) and (Forsberg & Ghysels, 2007) for recent empirical applications of the model.

In our analysis, we further generalize the multivariate HAR model by allowing the vector innovation term ($\boldsymbol{\varepsilon}_t$) to follow a multivariate GARCH process (VHAR-MGARCH). By extending the model in this manner, we are able to capture the volatility-of-volatility effect; i.e., an empirical observation that the volatility of volatility tends to increase (decrease) whenever volatility itself increases (decreases). While the idea is not new (Corsi, Mittnik, Pigorsch, & Pigorsch, 2008), our motivation for generalizing the model with an MGARCH structure is driven by recent findings that a univariate HAR-GARCH model fits very well the realized variances of the Central European exchange rates (Bubak & Zikes, 2009).

To model the dynamics of the conditional variance of the innovation process $\boldsymbol{\varepsilon}_t$ we employ the DCC model of (Engle R. F., 2002). In this model, the variance covariance matrix evolves according to

$$\boldsymbol{H}_t = \boldsymbol{D}_t \boldsymbol{R}_t \boldsymbol{D}_t,$$

where $\boldsymbol{D}_t = diag\left(h_{11,t}^{1/2}, \dots, h_{KK,t}^{1/2}\right)$, and $h_{ii,t}$ represents any univariate (G)ARCH(p,q) process, $i = 1, \dots, k$. The particular version of the dynamic conditional correlation model that we use is due to (Engle & Sheppard, 2001) and (Engle R. F., 2002). In this model, the correlation matrix is given by the transformation

$$\boldsymbol{R}_t = diag\left(q_{11,t}^{-1/2}, \dots, q_{KK,t}^{-1/2}\right)\boldsymbol{Q}_t diag\left(q_{11t}^{-1/2}, \dots, q_{KK,t}^{-1/2}\right),$$

where $\boldsymbol{Q}_t = \left(q_{ij,t}\right)$ in turn follows

$$\boldsymbol{Q}_t = (1 - \alpha - \beta)\overline{\boldsymbol{Q}} + \alpha\eta_{t-1}\eta_{t-1}^{'} + \beta\boldsymbol{Q}_{t-1},$$

where $\eta_t = \varepsilon_{i,t}/\sqrt{h_{ii,t}}$ are standardized residuals, $\overline{\boldsymbol{Q}} = T^{-1}\sum_{t=1}^{T}\eta_t\eta_t'$ is a k x k unconditional variance matrix of η_t, and α and β are non-negative scalars satisfying the condition that $\alpha + \beta < 1$. Recall that it is an ARMA representation of the conditional correlations matrix that guarantees the positive definiteness of $\boldsymbol{Q}_t$ and hence of $\boldsymbol{R}_t$.

To estimate the DCC-MGARCH model, we proceed as follows. First, we find a suitable specification for each of the four equations of the volatility transmission system as discussed earlier in this section. We continue in the usual way by iteratively removing from each equation the least significant variables until all the variables are significant. The DCC model is then fitted to the series of residuals, where the estimation is performed by optimizing the likelihood function using the Feasible Sequential Quadratic Programming (FSQP) algorithm of (Lawrence & Tits, 2001).[1] We estimate the model efficiently in one step to obtain valid standard errors for the DCC estimates.[2]

It is easy to see that the VHAR model can be written as a VAR(22) with restricted parameters. We can therefore employ the index of (Diebold & Yilmaz, 2009) to quantify the overall magnitude and evolution of volatility spillovers among the four foreign exchange markets. The Diebold-Yilmaz index is constructed as follows. Let $\boldsymbol{v}_t$ denote a k-dimensional random vector following a VAR(p) process with conditionally heteroskedastic innovations:

$$\boldsymbol{v}_t = \boldsymbol{c} + \boldsymbol{\Phi}_1\boldsymbol{v}_{t-1} + \boldsymbol{\Phi}_1\boldsymbol{v}_{t-1} + \cdots + \boldsymbol{\Phi}_p\boldsymbol{v}_{t-p} + \boldsymbol{\varepsilon}_t,$$

$$\boldsymbol{\varepsilon}_t = \boldsymbol{H}_t^{1/2}\boldsymbol{u}_t, \;\; \boldsymbol{u}_t \sim \mathrm{D}(\boldsymbol{0}, \boldsymbol{I}),$$

where $\boldsymbol{H}_t$ is a $\boldsymbol{F}_{t-1}$ measurable conditional covariance matrix. Provided that the VAR process is stationary, the moving-average representation exists and we can write

$$\boldsymbol{v}_t = \boldsymbol{\mu} + \boldsymbol{\varepsilon}_t + \boldsymbol{\Psi}_1\boldsymbol{\varepsilon}_{t-1} + \boldsymbol{\Psi}_2\boldsymbol{\varepsilon}_{t-2} + \cdots,$$

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[1] The FSQP algorithm is based on a sequential programming technique to maximize a non-linear function subject to non-linear constraints. See (Doornik, 2007) for more details on these two optimization functions.

[2] It is well known that the volatility and the correlation parts of the DCC-MGARCH system can be estimated consistently in two steps. However, the estimators obtained from two-step estimation are limited information estimators (see (Engle & Sheppard, 2001)) and hence are not fully efficient. In our estimation, we used the two-step estimation procedure to obtain accurate starting values for the one-step estimation. Note, however, that we performed both the one-step and the two-step estimations and the corresponding estimates were nearly identical.

see e.g. (Hamilton, 1994), Chapter 10. The optimal h-step ahead forecast is given by

$$\mathrm{E}_t(\boldsymbol{v}_{t+h}) = \boldsymbol{\mu} + \boldsymbol{\Psi}_h\boldsymbol{\varepsilon}_t + \boldsymbol{\Psi}_{h+1}\boldsymbol{\varepsilon}_{t-1},$$

and the forecast error vector, $\boldsymbol{e}_{t+h|t}$, is written as

$$\boldsymbol{e}_{t+h|t} \equiv \boldsymbol{v}_{t+h} - \mathrm{E}_t(\boldsymbol{v}_{t+h}) = \boldsymbol{\varepsilon}_{t+h} + \boldsymbol{\Psi}_1\boldsymbol{\varepsilon}_{t+h-1} + \boldsymbol{\Psi}_2\boldsymbol{\varepsilon}_{t+h-2} + \cdots + \boldsymbol{\Psi}_{h-1}\boldsymbol{\varepsilon}_{t+1}.$$

The corresponding conditional mean-square error matrix, $\boldsymbol{\Sigma}_{t+h|t}$, is given by

$$\boldsymbol{\Sigma}_{t+h|t} \equiv \mathrm{E}_t(\boldsymbol{e}_{t+h|t}\boldsymbol{e}'_{t+h|t}) = \mathrm{E}_t(\boldsymbol{H}_{t+h}) + \boldsymbol{\Psi}_1\mathrm{E}_t(\boldsymbol{H}_{t+h-1})\boldsymbol{\Psi}'_1 + \cdots + \boldsymbol{\Psi}_{\mathrm{h}-1}\boldsymbol{H}_{t+1}\boldsymbol{\Psi}'_{\mathrm{h}-1}.$$

Now define $\mathbf{Q}_{t+h|t}$ to be the unique lower triangular Choleski factor of $\mathrm{E}_t(\boldsymbol{H}_{t+h})$, and let

$$\mathbf{A}^{(i)}_{t+h|t} \equiv \boldsymbol{\Psi}_i\mathbf{Q}_{t+h-i|t}, \quad i = 0, \dots, h-1,$$

so we can write

$$\boldsymbol{\Sigma}_{t+h|t} = \mathbf{A}^{(0)}_{t+h|t}\mathbf{A}^{(0)'}_{t+h|t} + \mathbf{A}^{(1)}_{t+h|t}\mathbf{A}^{(1)'}_{t+h|t} + \cdots + \mathbf{A}^{(h-1)}_{t+h|t}\mathbf{A}^{(h-1)'}_{t+h|t}.$$

The time-varying Diebold-Yilmaz spillover index ($\mathbf{S}_{t+h|t}$) based on h-step ahead forecasts is then defined as

$$\mathbf{S}_{t+h|t} = \frac{\sum_{l=0}^{h-1}\sum_{\substack{i,j=1\\ i\neq j}}^{k}(a^{(l)}_{t+h|t}(i,j))^2}{\sum_{l=0}^{h-1}\mathrm{tr}(\mathbf{A}^{(l)}_{t+h|t}\mathbf{A}^{(l)'}_{t+h|t})}.$$

In the above definition $a^{(l)}_{t+h|t}(i,j)$ is a typical element of $\mathbf{A}^{(l)}_{t+h|t}$. If $\boldsymbol{H}_t$ follows a stationary MGARCH process, the forecasts $\mathrm{E}_t(\boldsymbol{H}_{t+h})$ can be obtained recursively.

The Diebold-Yilmaz index measures the proportion of the h-step ahead forecast error of own volatility that can be attributed to shocks emanating from other markets. In other words, the larger the fraction of h-step ahead forecast error variance in forecasting the volatility of market i that is due to shocks to market j relative to the total forecast error variation, the larger the value of the spillover index and hence the degree of volatility spillovers. In the case when there are no spillovers, the index is equal to zero.

4. Data

Our analysis is based on 5-minute spot exchange rate mid-quotes. We use EUR/USD quotes and quotes of the currencies of the three new EU members expressed in euro. The (exchange rate of the) currencies are the Czech koruna (EUR/CZK), the Hungarian forint (EUR/HUF), and the Polish zloty (EUR/PLN). The exchange rate quotes were collected over a period of 6.5 years between January 3, 2003 and June 30, 2009. The data for the three Central European currency pairs were obtained from Olsen Financial Technologies (Olsen). The data for the EUR/USD exchange rate were obtained from two sources: Electronic Broking

Services (EBS) for the period from January 3, 2003 to May 30, 2007, and Olsen for the period from May 30, 2007 to June 30, 2009.

The EBS Spot Dealing system is currently the largest and most liquid platform for trading the major currency pairs, covering about 60% of the average daily volume of EUR/USD trades. In contrast to data from Olsen, the EBS data is not filtered for erroneous observations, such as recording errors and displaced decimal points. Therefore, we employ the thorough data-cleaning procedure suggested by (Barndorff-Nielsen, Hansen, Lunde, & Shephard, 2008) in order to remove defective observations. In particular: (i) We delete all entries with missing bid or ask prices and entries for which either of the two are equal to zero. (ii) Then, we delete entries for which the bid-ask spread is negative or larger than 10 times the rolling centered median bid-ask spread, where the rolling window has a size of 50 observations. (iii) Finally, we delete entries for which the mid-quote deviates by more than 10 mean absolute deviations from the rolling centered median mid-quote, where the rolling window has a size of 50 observations.

Following the standard approach in the literature (Andersen T. G., Bollerslev, Diebold, & Labys, 2003), we further adjust the data by discarding weekend periods from Friday 21:00 GMT until Sunday 21:00 GMT, as well as major public holidays. The holidays include January 1 (New Year) and December 25 common to all four currency pairs, as well as December 26 (Christmas) and Easter Mondays, common only to the Central European currencies. These adjustments lead to a final sample of 1,673 trading days. It is important to note that this sample retains all other local holidays as most of the FX trading in the corresponding currencies is—at least during the European trading session—done in London.[3] Finally, following (Andersen T. G., Bollerslev, Diebold, & Labys, 2003), we define a trading day as the interval from 21:00 Greenwich Mean Time (GMT) to 20:59 GMT of the following day.

As a next step we construct the daily realized volatility. The construction of the realized volatility estimator differs between the Central European and EUR/USD currency pairs. First, as shown in (Bubak & Zikes, 2009), the Central European exchange rates are contaminated by market microstructure noise that leads to a substantial upward bias of the realized variance estimator when sampling at a 5-minute frequency. The microstructure noise appears to have a simple *i.i.d.* structure and thus we correct for it by employing the moving-average-based estimator of (Hansen, Large, & Lunde, 2008). Second, no microstructure noise has been identified in the 5-minute intraday returns of the EUR/USD exchange rate, similarly to (Chaboud, Chiquoine, Hjalmarsson, & Loretan, 2009). Consequently, no moving-average correction is necessary when constructing the realized variances of EUR/USD and we simply use equation (1).

Table 1 provides descriptive statistics for the daily realized variance and the logarithmic realized variance separately for each subsample of the data as employed in the empirical part of the study. The statistics point out similar characteristics of the four exchange rate series,

[3] In our analysis we include both exchange rate and UK-specific dummies in the volatility specifications to account for the lower liquidity resulting from (possibly) limited trading activity during these days.

although the Central European exchange rate returns exhibit on average a higher degree of skewness and kurtosis relative to EUR/USD. In addition, when measured by the sample standard deviation, the variance of the former currencies does not seem to be more volatile than that of EUR/USD although it tends to experience relatively larger swings as evidenced—especially during Period 1—by larger (absolute) minimum and maximum values. Figures 1 and 2 supplement this information with the plots of daily EUR/CZK, EUR/HUF, EUR/PLN, and EUR/USD spot exchange rates and the corresponding daily exchange rate returns for the whole sample period. It is interesting to note that the increased volatility that corresponds to the onset of the turbulent economic events and continues throughout 2009 parallels equally significant yet mutually opposite developments on the Central European and EUR/USD markets. Indeed, the Czech and Polish currencies initially experienced sharp depreciations and later, during the first months of 2009, all three currencies appreciated in unison. The US dollar, on other hand, experienced nearly the opposite development pattern over the same period.

One last note concerns the normality of the (logarithmic) realized variance. In Table 1 we show that both the realized variance as well as its logarithmic transformation exhibit levels of skewness and kurtosis far from those characterizing a normal distribution. To test the null hypothesis of the normality of the logarithmic realized variance explicitly, we employ a test based on the third and fourth Hermite polynomials (H34) with the Newey-West weighting matrix based on the methodology in (Bontemps & Meddahi, 2005). This test is valid in the presence of parameter uncertainty as well as dependence in the logarithmic realized variance. For Period 1, the test statistics for specific exchange rates are as follows: 95.8 (EUR/CZK), 46.8 (EUR/HUF), 41.5 (EUR/PLN) and 37.9 (EUR/USD). As the null hypothesis is rejected for each exchange rate, none of the logarithmic realized variance series follow a normal distribution during this period. In contrast, the statistics read 8.4, 3.8, 18.8, and 7.2 for Period 2, in which case we cannot reject the null hypothesis of normality for EUR/PLN and at 2.7% neither can we for EUR/USD. The logarithmic transformation of the realized variance therefore does not follow a normal distribution during the longer period of 2003–2007 but seems to be closer to normal during the shorter period of 2008–2009.

Finally, Figure 2 (left column) provides a general view of the dynamics of the realized variance over the entire sample. The overall pattern follows the major events that the currencies experienced since 2003. Aside from influence of major events volatility increases for those countries with troubled development of their financial sector (eg. Hungary). The plots of the autocorrelation function of the logarithmic realized variance (right column) show very slow decays consistent with a very persistent, long-memory type of dynamics.

5. Empirical Results

Before presenting our results we briefly review the dynamics of the round-the-clock trading activity on the FX markets studied. This will help us understand the specific intraday pattern that characterizes the volatility of Central European and EUR/USD currency pairs. Further, it sets a framework for a more accurate interpretation of the empirical results concerning volatility transmission between EUR/USD and the Central European foreign exchange markets.

The international scope of currency trading requires that foreign exchange markets operate on a 24-hour basis. A typical trading day consists of three major sessions (see Figure 3), corresponding roughly to the opening and closing hours of the major foreign exchange markets in London, New York, and Tokyo. In particular, the sessions and associated time zones are: the European session (7:00–17:00 GMT), the U.S. session (13:00–22:00 GMT) and the Asian session (0:00–9:00 GMT). See (Lien, 2008) for a more thorough discussion of the trading sessions.

The changes in trading activity induced by these three sessions are crucial for the evolution of the instantaneous volatility process over the course of the trading day, both for the Central European and the EUR/USD currency pairs. The plots in Figure 4 illustrate the evolution of the intraday volatility for each of the four currency pairs. Specifically, the plots depict the evolution of the 30-minute realized variance computed for each of the 48 intraday 30-minute intervals and then averaged over the whole sample and smoothed by a cubic spline.

We first discuss the plots corresponding to the Central European currency pairs. The trades in the CE currencies are primarily executed during the European session. The first spike in the volatility of the CE currencies occurs during the morning hours of trading. After an active morning, trading slows down around lunch time, with a decrease in volatility of 40 to 50 percent relative to the morning peak. Then, however, large banks and institutional investors are finished repositioning their portfolios and, in anticipation of the opening of the U.S. market, start converting European assets into USD-denominated ones (Lien, 2008). The volatility continues to rise during the overlapping hours of the European and U.S. sessions (13:00–17:00 GMT), forming the second significant peak in the intraday volatility pattern, before decreasing considerably during the overnight period.

The euro/dollar trading (bottom right part of Figure 4) shows three peaks. The first peak corresponds to the most active trading hours of the Asian session (1:00–5:00 GMT), the second peak is due to the closing of the Asian markets as well as the first half of the trading day in London and, finally, the main peak represents the most volatile session when the U.S. and European sessions overlap (13:00–17:00 GMT). The morning hours in the U.S. are marked by the execution of the majority of the transactions occurring during the entire U.S. trading session, as European traders are still active in the market. The trading continues even after the end of the European session (17:00–22:00 GMT), but the activity winds down to a minimum soon thereafter, until the opening of the Tokyo market during the early morning hours of the next day.

As concerns holidays, we find that days of low volatility in the CEE markets are typically associated with the UK bank holidays, with a limited relation to the holidays relevant to a given Central European country. This confirms the dominance of the London market.

5.1. Sample Periods and Granger Causality Tests

We perform an analysis of volatility transmission separately for the period from January 2, 2003 to December 30, 2007 (Period 1) and for the period from January 2, 2008 to June 30, 2009 (Period 2) as we find that the underlying volatility series behave very differently across the two sample periods. To determine the timing of the structural break we run a recursive estimation of the VHAR model (available from the authors upon request). The parameter estimates exhibit very stable behavior up to the end of 2007. Extending the sample period further, however, results in quite erratic changes in the estimated parameters and we thus choose to split the sample at this point. All tests and estimations are then carried out separately for the two sub-samples.

We start by interpreting the results of the Granger causality tests (Table 2) as applied to the coefficient estimates from the full (unrestricted) models. Columns 1 to 4 of Table 2 report the Granger causality tests for the model estimated for Period 1. We find that the lagged realized variance components of the Hungarian forint and U.S. dollar seem to play an important role in determining the volatility of the Czech koruna and Polish zloty. On the other hand, we find that the current volatility of neither EUR/CZK nor EUR/PLN seem to carry statistically significant information about the future volatility of the other two currencies.

Turning our attention to the EUR/HUF equation, we observe that the Hungarian forint is largely weakly exogenous as the tests indicate no significant Granger causality running from any of the other three exchange rates. We conjecture that this result is due to heightened concerns of the Hungarian Central Bank about the exchange rate of the forint. First, forint depreciation increases risk of not fulfilling inflation target. Second, many Hungarian private subjects have loans denominated in foreign currencies and forint depreciation increases risk of corporate and households default as theses subjects have income in forint but debt related expenditures in foreign currencies. We finally note the statistically significant contribution of the EUR/CZK variance to the future volatility of the U.S. dollar. This is a rather puzzling causal pattern.

The Granger causality tests for the model estimates based on Period 2 (columns 5 to 8) seem to suggest that during the increased market uncertainty that characterized this period, the volatilities of Central European currencies seemed to be less responsive to the variance components of the other exchange rates compared to the pre-2008 period (Period 1). In particular, we find that the Czech koruna is the only CE currency that seems to be significantly affected by the lagged EUR/USD variance components. No further Granger causality is found.

5.2. Volatility Transmission Model

Having discussed the results of the Granger causality tests we now shed more light on the pattern of volatility transmission by estimating the VHAR-GARCH model. In addition to the variance components of the relevant exchange rates, two dummy variables enter the right-hand side of the VHAR models: a dummy variable that represents the domestic holidays relevant for the dependent variable, d, and a dummy variable for UK bank holidays, d_{UK}.[4] These dummies help capture the drop in volatility associated with low trading activity during holiday periods and ensure that the dynamic parameter estimates are not biased by the presence of holidays in the sample.

Furthermore, we divide the lagged daily realized volatility of EUR/USD into two parts: the first component captures the realized volatility between 21:00 GMT and 17:00 GMT of the next day, while the second component captures the remaining part of the daily realized volatility, i.e. the period spanning 17:00–21:00 GMT. The motivation for allowing these two components to enter the volatility transmission model separately comes from the analysis of the intraday volatility pattern documented in Figure 4. Specifically, we find that the CE currencies exhibit little variability during the second period (17:00–21:00 GMT) when the EUR/USD is still actively traded in the U.S. It is therefore interesting to investigate whether it is this part of the EUR/USD daily volatility that spills over into the next day's volatilities of the CE exchange rates, which would be consistent with the meteor shower hypothesis of (Engle, Ito, & Lin, 1990).

The estimation results for the volatility transmission model are reported in Table 3. We present the estimates for the two sub-samples separately and to save space only report the restricted models, that is, models in which insignificant right-hand side variables have been successively eliminated. Starting with Period 1 and the equation for EUR/CZK we observe that in addition to the information contained in its own three components, the current volatility of EUR/CZK is significantly affected by the short-term and long-term variance components of EUR/HUF ($\beta_{1,HU}$ and $\beta_{22,HU}$, respectively), as well as by the long-term variance component of the EUR/USD exchange rate, $\beta_{22,US}$. However, the signs and the magnitudes of the coefficient estimates differ fundamentally across the various components.

In particular, we find that among the own-variance components, the medium term variance component, $\beta_{5,CZ}$, seems to have the largest impact in terms of magnitude, followed by the long-term and short-term components ($\beta_{22,CZ}$ and $\beta_{1,CZ}$, respectively). In each instance, the impact is positive. Relatively smaller but also positive is the effect corresponding to the short-term component of the EUR/HUF, $\beta_{1,HU}$. However, we find a similarly large but negative impact of the long-term variance component of the same currency. Finally, we observe that the long-term component of EUR/USD, $\beta_{22,US}$, has a positive effect on the present volatility of EUR/CZK of the magnitude similar to that of its own short-term component.

As for the EUR/HUF variance equation, we note that other than its own three variance components, only the medium-term variance component due to EUR/CZK, $\beta_{5,CZ}$, affects the present volatility of EUR/HUF during 2003–2008. A point worth noting is the order of importance of the own-variance components. Clearly, the medium term variance has the

[4] Exact information on UK holidays was obtained from the relevant governmental site: http://www.direct.gov.uk. In line with tradition, bank holidays include UK public holidays as well as the so-called "substitute days" that normally occur on the Monday following the date when a bank or public holiday falls on a Saturday or Sunday.

largest impact with $\beta_{5,HU}$ = 0.344, followed closely by the coefficient estimate on the short-term component, $\beta_{1,HU}$. The long-term component, $\beta_{22,HU}$, happens to be by far the least important of the three in terms of magnitude.

The case of EUR/PLN is slightly more interesting. Evident is a relatively small but positive effect on the present volatility of EUR/PLN of the short-term component due to EUR/HUF, $\beta_{1,HU}$, as well as a positive impact of the long-term component due to the same currency, $\beta_{22,HU}$. As in case of EUR/HUF, we again observe a large importance of the medium-term own variance component, $\beta_{5,PL}$; this time, however, it is closely followed by the short-term and only remotely by the long-term variance components, with the corresponding coefficient estimates reading $\beta_{22,PL} = 0.307$ and $\beta_{1,PL} = 0.206$, respectively. Finally, the long-term variance component of EUR/USD also positively affects the current volatility of EUR/PLN.

The results for the USD equation reveal a statistically significant impact of the medium- and long-term variance components of EUR/CZK ($\beta_{5,CZ}$ and $\beta_{22,CZ}$, respectively). Note also that we observe no effect on the present volatility of EUR/USD of the part of its own short-term variance component, $\beta_{11,US}$, generated during the U.S. trading session just ahead of the close of the European session (17:00 GMT of the previous day). Instead, only the part of the short-term variance component generated after the close of the European session is found to be statistically significant.

With respect to the two dummy variables for the local and UK holidays, we find the former to be statistically insignificant across the variance equations for all of the Central European exchange rates, while the latter dummy is found to be is highly statistically significant in all but one case (HUF). These results are in line with our previous discussion that pointed to a limited effect of domestic holidays on the trading of the corresponding currencies. For the same reason, UK bank holidays are days when the trading activity in these currencies slows down considerably.

The results for Period 2 (January 2003 to June 2009) are reported in columns 6 to 9 for the four currencies of the restricted equation system. We focus on major differences in the impact of different variance components relative to Period 1. In the case of the EUR/CZK exchange rate, we observe that it is not the combination of the short- and long-term components of EUR/HUF that affects its current volatility, instead, the medium- to long-term coefficients seem to carry significant information for the current volatility of EUR/CZK. We also find that during the relatively more volatile Period 2, the EUR/CZK currency does not respond to any EUR/USD variance component anymore, except for part of the (immediately preceding) short-term variance component of EUR/USD, $\beta_{11,US}$, generated after the close of the European session. As far as the own-variance components are concerned, we find no contribution of the medium-term own-variance component on the present volatility of EUR/CZK. On the other hand, both the short-term and the long-term variance components increase in magnitude relative to Period 1, the latter almost three times. Finally, the CZK dummy is significant during Period 2.

In the EUR/HUF equation, we find that it is the short- to medium-term own variance components that play the most significant role in explaining the currencies' current volatilities. Perhaps surprisingly, the short-term variance component of EUR/PLN becomes significant during Period 2, revealing the importance of EUR/PLN during an extended period of economic crisis.

The results for EUR/PLN are notable for the lack of any non-own-variance components. Instead, we observe an increase in the importance of both short- and medium-term own-variance components relative to Period 1, alongside a relative decrease in the magnitude of the effect of the long-term own-variance component on the present volatility of EUR/PLN. Unlike the first period, there is no impact of the lagged EUR/HUF variance.

The coefficient estimates for the EUR/USD equation are far from similar to those obtained during Period 1. Specifically, we notice that this time both of the short-term own-variance components are present, with part of the component generated during the U.S. trading session, $\beta_{11,US}$, becoming highly significant. At the same time, the long-term own-variance component is found to have no effect on the present volatility of EUR/USD.

Panel B (Table 3) presents the ARCH and GARCH estimates for each equation of the system along with a battery of basic diagnostic tests (Panel C). We notice that the GARCH estimates are similar for Period 1 and 2, with the largest level of volatility persistence found in the case of EUR/PLN and the lowest in the case of EUR/HUF. The residual diagnostics performed on the simple and squared standardized residual series from the HAR-GARCH equations confirm that most of the univariate specifications provide a reasonable fit to the underlying volatility process. In the case of EUR/USD (and marginally also of EUR/CZK) in Period 1, the large value of the Ljung-Box statistics suggests the presence of serial correlation in the standardized residual series; nevertheless, a simple plot of the autocorrelation function for the relevant residual series (Figure 5) reveals no obvious dependence patterns as the series appears to be *i.i.d.*[5] In any case, the inference based on the Ljung-Box Q statistics remains limited also due to the presence of heteroskedasticity. Finally, we note that Engle's LM test provides evidence of no remaining ARCH effects in the residual series.

A final note concerns the evolution of pairwise conditional correlations over time. Figure 6 shows the correlations implied by the DCC model as estimated for Period 1. (Recall that a CCC model was fit to Period 2.) We observe a rather volatile evolution of conditional correlations for most of the exchange rate pairs, although in most cases the correlations remain bounded between 0 and 0.3 over the sample period.

5.3. Spillover Index

[5] The disproportionately large contribution of some of the lags (e.g., lags 8 and 22 for EUR/USD) may bear witness to a certain inflexibility of the standard HAR model. To this end, we have tried several specifications, including a series of unrestricted VHAR(p) models with up to 30 lags of the dependent variable in the mean equation(s). In the least parsimonious models, the Q statistics became insignificant but any gains in fit seemed insufficient to justify the resulting loss of parsimony.

Figure 7 plots the spillover index over time for different forecast horizons. We consider 1-day, 5-day and 22-day forecast horizons, reflecting the lengths of the corresponding one day, one week and one month variance components in the HAR equations. A number of interesting observations can be made.

First, we note that, although quite volatile, the plot of the spillover index clearly reveals all the major periods of increased volatility spillovers. These include, among others, the onset of a dollar crisis in March 2005, or a sharp rise in foreclosures in the U.S. subprime mortgage market that hit globally in July 2007. Similarly to the other critical market events driving the plot's dynamics, we observe that the volatility spillovers increase from anywhere between 40 to 80 percent in these instances. Second, the forecast horizon does not play an important role in terms of the level of volatility spillovers, although relative to the immediate (short-term) effect, the spillovers seem to attenuate in the long term.

6. Conclusion

In this paper, we analyze the nature and dynamics of volatility spillovers between Central European and EUR/USD foreign exchange markets. In contrast to the majority of the existing empirical literature, our work relies on model-free non-parametric measures of ex-post volatility based on high-frequency (intraday) data. We formulate a flexible yet parsimonious parametric model in which the realized volatility of the given exchange rate is driven both by its own history as well as the volatilities of other exchange rates of the system realized over different time horizons. Given the multivariate framework, the model helps us study both qualitative and quantitative repercussions of short-term and/or long-term volatility components characterizing one foreign exchange market on the evolution of another.

Our empirical results document the existence of volatility spillovers between the Central European foreign exchange markets on an intraday basis. We find that each Central European currency has a different volatility transmission pattern. For example, during the pre-2008 period, the current volatilities of both the EUR/CZK and EUR/PLN exchange rates are affected by—other than their own histories—both the short-term and long-term volatility components of EUR/HUF as well as by the long-term volatility component of EUR/USD. In contrast, EUR/HUF seems irresponsive to any foreign component other than the medium-term volatility component of EUR/CZK in addition to its own. In addition, EUR/HUF is also the only Central European exchange rate that is not significantly affected by the volatility of EUR/USD. To facilitate our study of the magnitude and behavior of volatility spillovers over time, we also formulate a dynamic version of the Diebold-Yilmaz spillover index (Diebold & Yilmaz, 2009). By plotting the index in time, we find the magnitude of the volatility spillovers increases significantly during periods of market uncertainty. From a medium-term perspective volatility increases for those countries with troubled development of their financial sector (eg. Hungary).

Our results on volatility transmission augment the literature on developed foreign exchange markets and fill the void on emerging markets in Europe. Uncovered differences in volatility patterns and their drivers lend new insights into trading strategies assessed by (de Zwart, Markwat, Swinkels, & van Dijk, 2009). Further, the synthesis of our findings is also relevant from the perspective of research on investment strategies as (Groh & von Liechtenstein, 2009) show that all of the three countries under research score high in terms of attractiveness for risk-capital investors. In further research we aim to analyze volatility transmission during the post-crisis period as new data become available.

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Table 1. Descriptive Statistics

Descriptive statistics for daily realized variance and daily logarithmic realized variance. In the case of the Central European currencies (EUR/CZK, EUR/HUF, EUR/PLN), the realized variance is calculated using a moving-average estimator. The Period 1 sample runs from January 3, 2003 to December 30, 2007 and Period 2 from January 2, 2008 to June 30, 2009.

		Mean	Std Dev	Skew	Kurt	Min	Max
Period 1							
CZK	RV_t	0.107	0.124	14.45	318.8	0.010	3.180
	$\log(RV_t)$	-2.452	0.610	0.466	4.522	-4.654	1.157
HUF	RV_t	0.259	0.437	11.90	214.7	0.001	9.447
	$\log(RV_t)$	-1.786	0.868	0.232	4.463	-6.620	2.246
PLN	RV_t	0.313	0.269	4.141	35.51	0.027	3.491
	$\log(RV_t)$	-1.413	0.701	0.042	3.128	-3.602	1.250
USD	RV_t	0.306	0.190	2.950	28.10	0.012	2.765
	$\log(RV_t)$	-1.349	0.590	-0.280	3.430	-4.433	1.017
Period 2							
CZK	RV_t	0.594	0.618	2.706	14.20	0.050	5.152
	$\log(RV_t)$	-0.926	0.887	0.284	2.340	-2.993	1.639
HUF	RV_t	1.211	1.622	4.532	32.77	0.076	16.48
	$\log(RV_t)$	-0.329	1.003	0.205	2.582	-2.572	2.802
PLN	RV_t	1.208	1.460	2.130	9.254	0.047	10.27
	$\log(RV_t)$	-0.575	1.330	-0.000	1.757	-3.050	2.329
USD	RV_t	0.863	0.749	2.112	9.290	0.073	5.492
	$\log(RV_t)$	-0.459	0.790	0.131	2.375	-2.623	1.703

Table 2. Granger Causality Tests

Results of the tests for the significance of groups of coefficients. The rows correspond to the equations of the system estimated for the exchange rate shown in the left column. Columns 1–4 report the tests based on the models estimated for Period 1 (January 2, 2003 to December 30, 2007) and columns 5–8 the estimates for Period 2 (January 2, 2008 to June 30, 2009). Similarly, the columns represent the groups of coefficients related to the exchange rate shown in the top row whose joint significance in the given equation is tested. The reported F-statistics are the Wald statistics for the joint null hypothesis that $\beta_1 = \ldots = \beta_{22} = 0$. An asterisk (*) denotes the cases where the null hypothesis is rejected at the 5% significance level. Superscript c corresponds to 10% level.

	Period 1: Jan 2, 2003 - Dec 30, 2007				Period 2: Jan 2, 2008 - Jun 30, 2009			
	CZK	HUF	PLN	USD	CZK	HUF	PLN	USD
CZK	–	3.913*	0.780	3.355*	–	0.640	1.554	2.414*
		(0.009)	(0.505)	(0.010)		(0.590)	(0.200)	(0.049)
HUF	2.234^c	–	1.419	0.525	0.198	–	2.476^c	0.521
	(0.083)		(0.236)	(0.718)	(0.898)		(0.061)	(0.720)
PLN	0.191	6.785*	–	2.709*	1.436	1.734	–	0.774
	(0.903)	(0.000)		(0.029)	(0.232)	(0.160)		(0.543)
USD	4.159*	1.035	0.536	–	1.217	1.274	2.069	–
	(0.006)	(0.376)	(0.658)		(0.303)	(0.283)	(0.104)	

Table 3. Estimation Results

Parameter estimates and diagnostics for the final (restricted) equations of the volatility transmission models. Columns 1–4 report estimates based on Period 1 (January 2, 2003 to December 30, 2007) and columns 5–8 the estimates based on Period 2 (January 2, 3008 to June 30, 2009). There are a total of 1,266 and 385 observations for Period 1 and Period 2, respectively. The corresponding *t*-statistics (in parentheses) are computed using White's heteroskedasticity-consistent standard errors. Parameters α and β denote the ARCH and GARCH coefficient estimates, respectively, from the volatility part of the model (the constant estimate from the volatility equation is not shown). *Q*(60) represents the Ljung-Box *Q*-statistics for the null hypothesis of no autocorrelation up to lag 60 in the raw standardized residuals from the DCC (CCC) model. Similarly, LM(20) represents Engle's LM test for ARCH effects up to lag 20 in the same series. For both tests, the *p*-values are given in parentheses.

	Period 1: Jan 2, 2003 - Dec 30, 2007				Period 2: Jan 2, 2008 - Jun 30, 2009			
	CZK	HUF	PLN	USD	CZK	HUF	PLN	USD
Panel A.: Mean Equation								
Cons	-0.755	-0.417	-0.157	0.231	0.149	0.019	0.007	0.255
	(-5.306)	(-3.702)	(-2.545)	(2.626)	(1.835)	(0.671)	(0.246)	(3.682)
$\beta_{1,CZ}$	0.181				0.287			
	(4.524)				(4.443)			
$\beta_{5,CZ}$	0.252	-0.085		-0.115				
	(4.082)	(-2.140)		(-3.229)				
$\beta_{22,CZ}$	0.194			0.159	0.585			
	(2.208)			(3.060)	(5.576)			
$\beta_{1,HU}$	0.105	0.327	0.069			0.229		
	(4.109)	(6.927)	(3.166)			(3.798)		
$\beta_{5,HU}$		0.344			0.222	0.470		
		(5.374)			(3.045)	(6.493)		
$\beta_{22,HU}$	-0.139	0.209	-0.131		-0.254			
	(-4.025)	(3.794)	(-4.250)		(-2.793)			
$\beta_{1,PL}$			0.206			0.169	0.299	
			(6.171)			(3.905)	(4.832)	
$\beta_{5,PL}$			0.314				0.500	0.118
			(5.326)				(4.936)	(3.628)
$\beta_{22,PL}$			0.307				0.173	
			(4.563)				(2.308)	
$\beta_{11,US}$								0.284
								(4.536)
$\beta_{21,US}$				0.091	0.095			0.111
				(5.775)	(2.998)			(3.314)
$\beta_{5,US}$				0.390				0.325
				(7.194)				(3.464)
$\beta_{22,US}$	0.166		0.142	0.429				
	(3.582)		(2.676)	(7.165)				

Table continues on the next page.

	Period 1: Jan 2, 2003 - Dec 30, 2007				Period 2: Jan 2, 2008 - Jun 30, 2009			
	CZK	HUF	PLN	USD	CZK	HUF	PLN	USD
D				-0.716	-0.385			-0.391
				(-10.26)	(-2.314)			(-4.954)
d_{UK}	-0.283	-0.421	-0.504	-0.620	-0.816	-0.804	-0.558	-0.773
	(-1.965)	(-1.900)	(-5.561)	(-4.588)	(-3.230)	(-10.31)	(-2.755)	(-4.098)
Panel B.: Variance Equation								
α	0.054	0.073	0.011	0.108	0.078	0.025	0.034	0.065
	(2.680)	(2.819)	(8.069)	(2.047)	(1.676)	(1.083)	(0.909)	(1.958)
β	0.925	0.688	0.950	–	–	0.899	0.711	0.822
	(32.47)	(8.069)	(20.87)			(18.71)	(5.065)	(12.79)
Panel C.: Diagnostics								
R^2	0.268	0.487	0.549	0.606	0.709	0.736	0.857	0.795
$Q(60)$	80.77	68.10	52.57	93.91	46.05	61.51	60.77	75.03
	(0.011)	(0.129)	(0.530)	(0.001)	(0.800)	(0.318)	(0.342)	(0.046)
$LM(20)$	25.69	15.19	25.53	14.65	3.959	10.82	21.30	11.41
	(0.176)	(0.766)	(0.182)	(0.796)	(0.999)	(0.951)	(0.379)	(0.935)

Table 4. MGARCH Parameter Estimates

Coefficient estimates from the multivariate part of the MGARCH model based on Period 1 (January 2, 2003 to December 30, 2007) and Period 2 (January 2, 3008 to June 30, 2009). The model for Period 1 was estimated as a DCC-MGARCH model. Recall that in the DCC model we employ (Engle & Sheppard, 2001), the conditional correlation matrix follows

$$\boldsymbol{Q}_t = (1-\alpha-\beta)\overline{\boldsymbol{Q}} + \alpha_{DCC}\eta_{t-1}\eta_{t-1}' + \beta_{DCC}\boldsymbol{Q}_{t-1},$$

hence the coefficients α_{DCC} and β_{DCC} in the *Coefficient Part* of the table. A CCC-MGARCH model was employed for the estimation of Period 2 as the null hypothesis of constant conditional correlation model was not rejected either by the LM Test of (Tse, 2000) or the (Engle & Sheppard, 2001) test for dynamic correlation at any reasonable level of significance. Unless stated otherwise, all coefficients are significant at the 1% level. Superscript *b* denotes significance at the 5% level. The parentheses present robust *t*-values.

	Correlation Part						*Coefficient Part*	
	ρ_{21}	ρ_{31}	ρ_{41}	ρ_{32}	ρ_{42}	ρ_{43}	α_{DCC}	β_{DCC}
Period 1	0.160	0.161	0.088^b	0.380	0.200	0.257	0.012	0.950
	(3.888)	(4.412)	(2.319)	(11.22)	(5.551)	(6.827)	(2.701)	(39.87)
Period 2	0.252	0.357	0.210	0.511	0.297	0.336	–	–
	(4.812)	(7.517)	(4.553)	(12.89)	(5.073)	(7.644)		

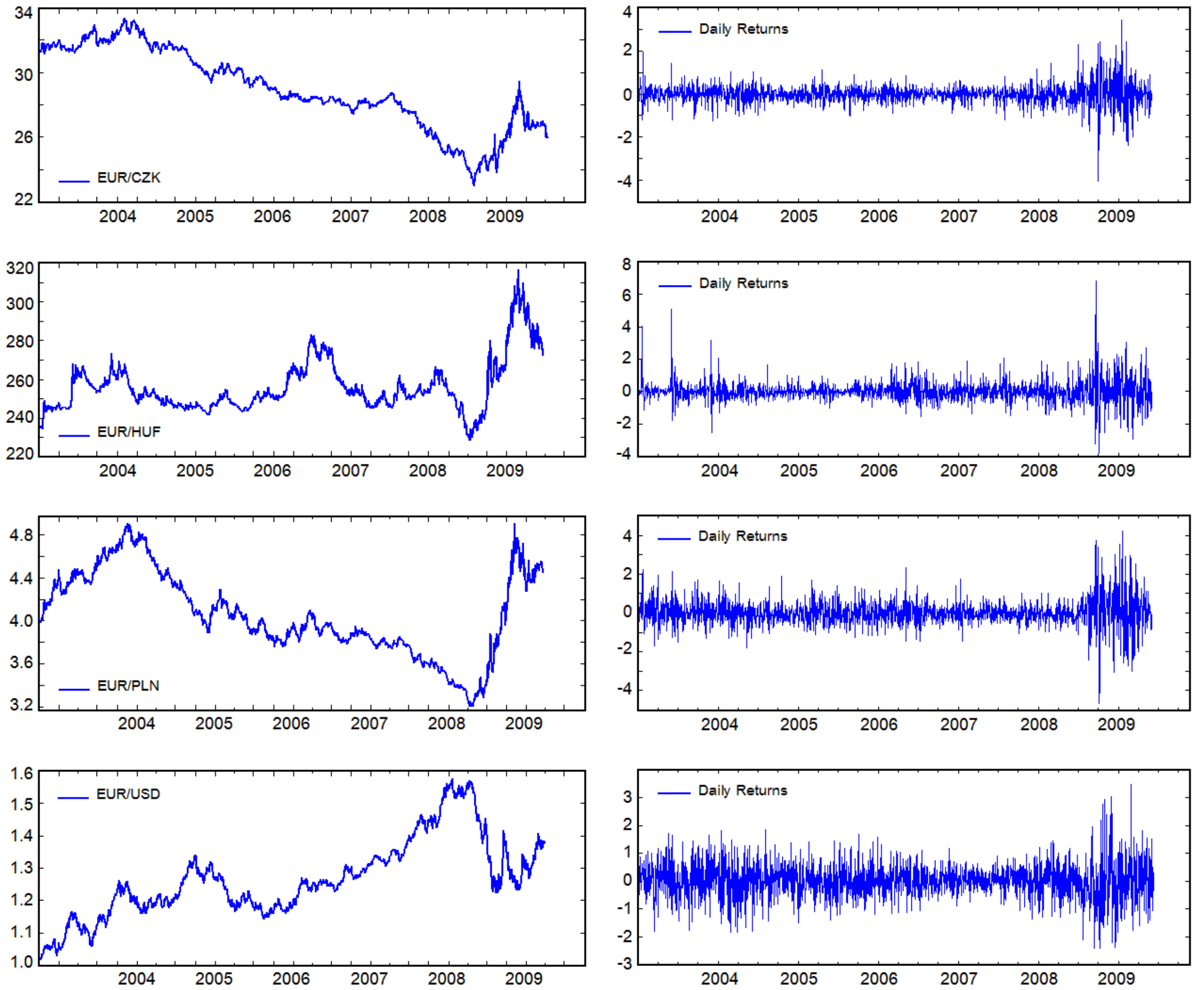


Figure 1.: Plots of daily spot rates (left) and daily returns (right) for the case of EUR/CZK (first row), EUR/HUF (second row), EUR/PLN (third row) and EUR/USD (last row) exchange rates. The sample runs from January 3, 2003 to June 30, 2009.

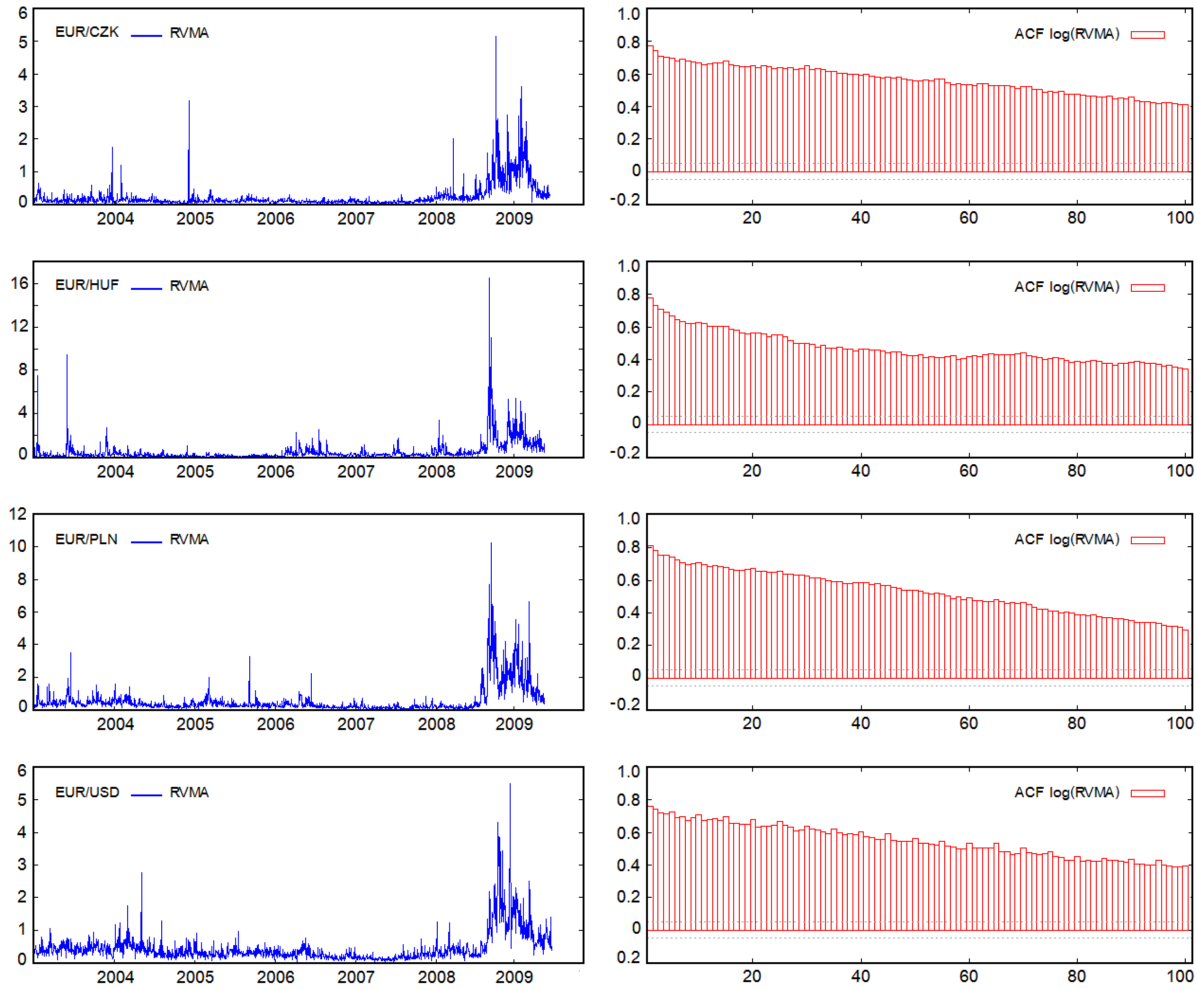


Figure 2.: Plots of daily realized volatility (RV) (left) and ACF of log(RV) (right) for the case of EUR/CZK (first row), EUR/HUF (second row), EUR/PLN (third row) and EUR/USD (last row) exchange rates. The sample runs from January 3, 2003 to June 30, 2009.

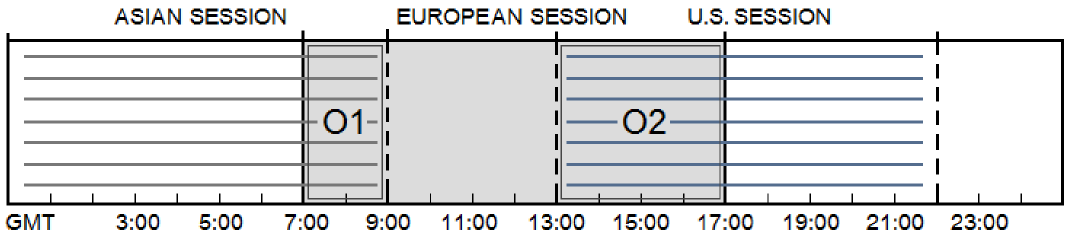


Figure 3.: Major Forex trading sessions. The hours at the bottom of the figure correspond to Greenwich Mean Time (GMT). Mnemonic "O1" denotes the period of overlapping Asian and European sessions (7:00–9:00 GMT) and "O2" the period of overlapping European and U.S. sessions (13:00–17:00 GMT).

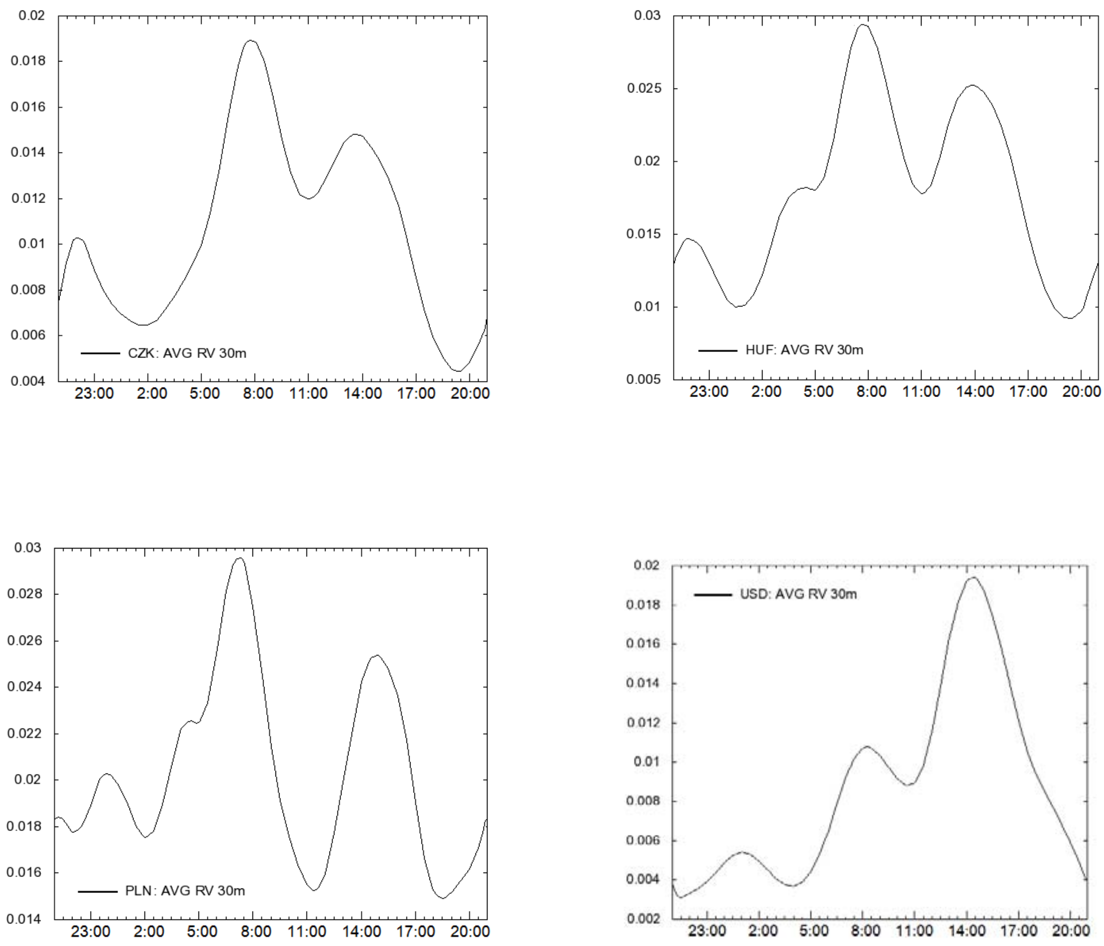
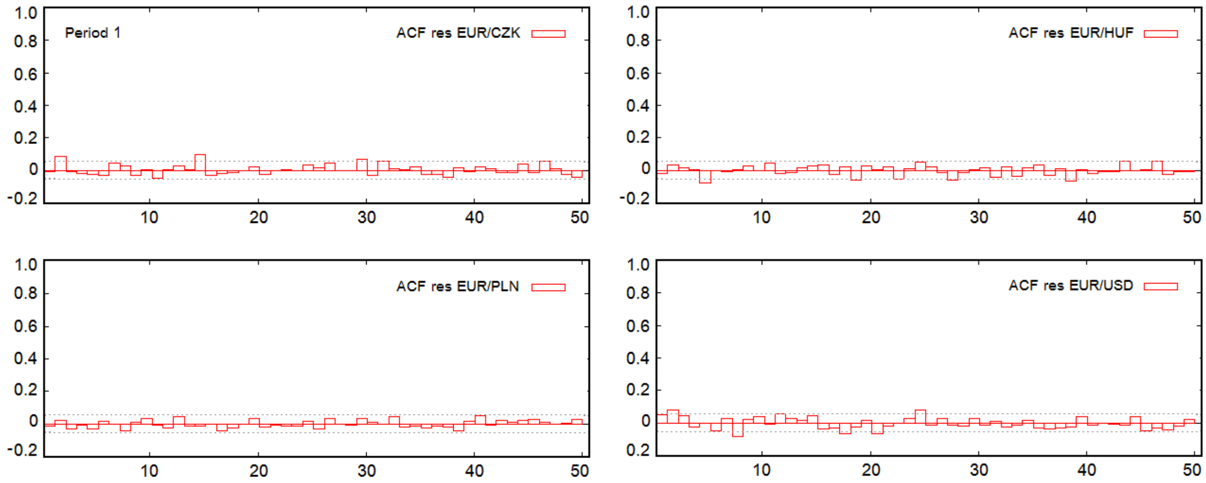
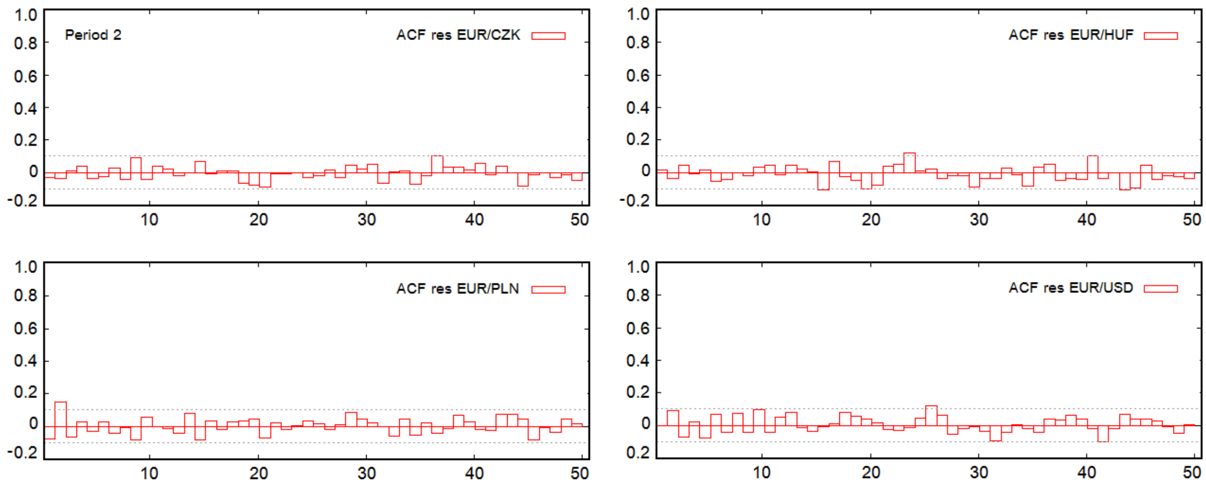


Figure 4.: An intraday evolution of realized volatility for EUR/CZK (top left), EUR/HUF (top right), EUR/PLN (bottom left) and EUR/USD (bottom right) exchange rates. The realized volatility is computed over 30-minute intraday intervals starting at 21:00h on day (*t*–1) and ending at 21:00h on day (*t*) and then averaged across each interval over the whole sample. The hours at the bottom part of the figure are in GMT.



Period 1.



Period 2.

Figure 5.: ACF plots of standardized residuals from the MGARCH model as estimated for Period 1 (January 2, 2003 to December 30, 2007) on the upper four plots, and for Period 2 (January 2, 2008 to June 30, 2009) on the lower four plots.

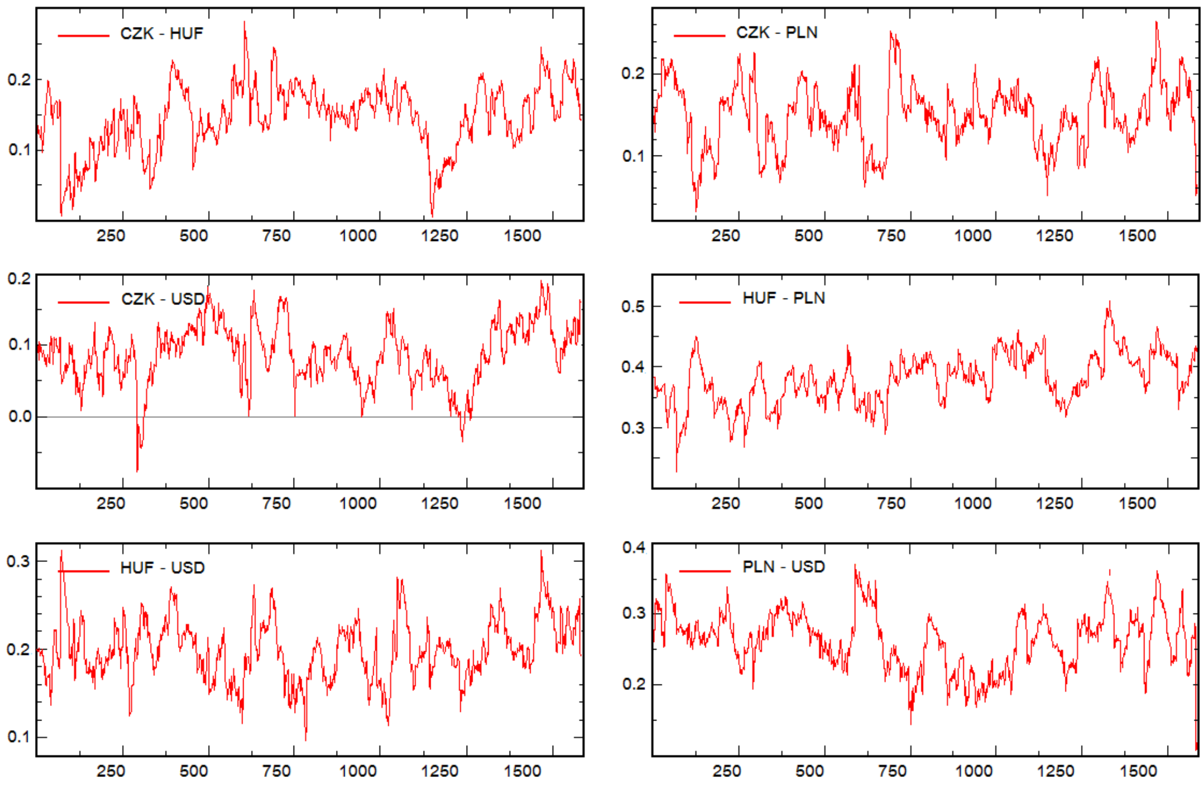


Figure 6.: Plots of conditional correlations as implied by the DCC-MGARCH model estimated for Period 1 (January 2, 2003 to December 30, 2007) for the four exchange rate currency pairs analyzed in the study.

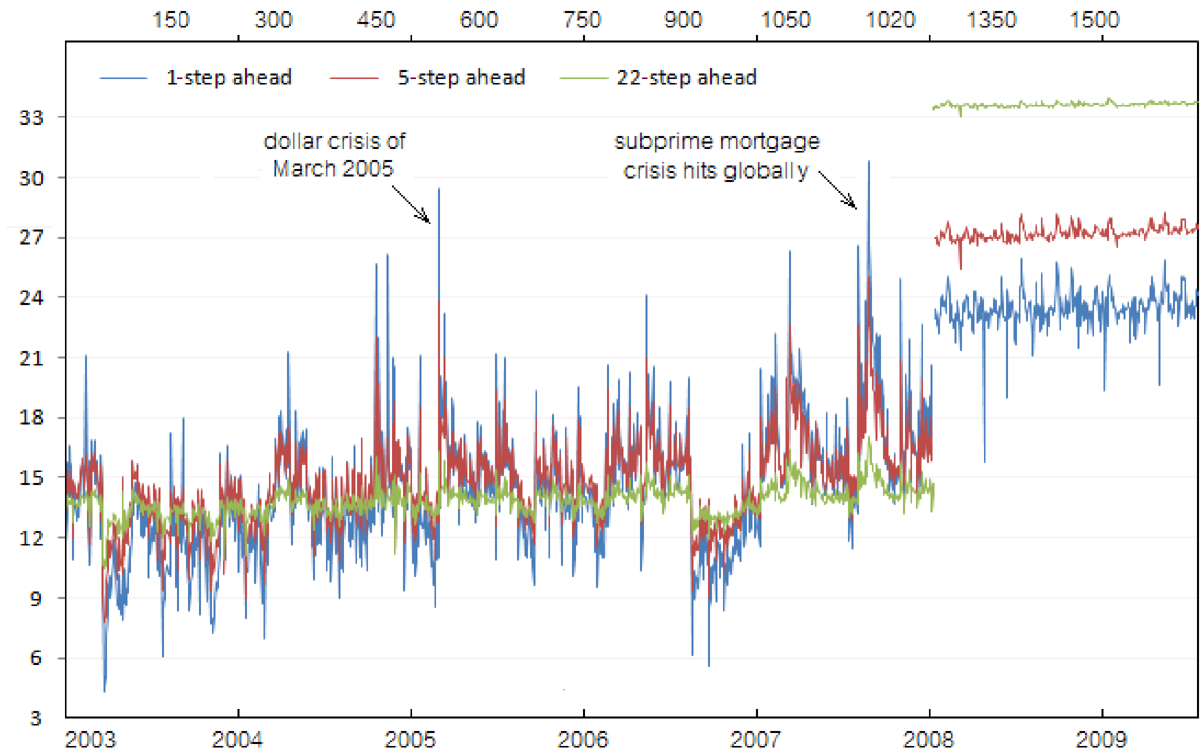


Figure 7.: The volatility spillover plot. At any point in time, the volatility spillover index is defined as the sum of all contributions to the forecast error variances of currency pair *i* generated by innovations to currency pair *j*, added across all *i*'s. The top of the figure includes the number of observations.

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