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Volatility transmission in emerging European foreign exchange markets

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Abstract

This paper studies the dynamics of volatility transmission between Central European (CE) currencies and the EUR/USD 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 CE foreign exchange markets. With the exception of the Czech and, prior to the recent turbulent economic events, Polish currencies, we find no significant spillovers running from the EUR/USD to the CE 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 classification: C5; F31; G15
Keywords: Foreign exchange markets; Volatility; Spillovers; Intraday data; Nonlinear dynamics; European emerging markets

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1. Introduction

The financial and economic turbulence during 2008–2009 renewed interest in understanding the nature of contagion effects among financial markets (Aloui et al., 2011). The recent economic crisis included a significant fall in asset prices along with large and unexpected movements in foreign exchange rates (Muller and Verschoor, 2009). The crisis deeply affected the financial sectors in Europe (Moshirian, 2011), not excluding European emerging markets. 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 CE currencies is of key importance for international investors contemplating the diversification benefits of allocating part of their portfolio to CE assets. In fact, according to Jotikasthira et al. (2010), developed-country-domiciled mutual and hedge fund holdings already account for about 13–19% of the free-float adjusted market capitalization in Central Europe (16.6% in the Czech, 17% in the Hungarian and 13.3% in the Polish equity markets). Since international stock market co-movements tend to be stronger in periods of distress and therefore high volatility (King and 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 et al. (2009).

Further, there are even more fundamental reasons to be interested in analyzing volatility transmission in European emerging markets. The new EU members committed themselves to adopting the euro upon satisfying the set of Maastricht convergence criteria, one of which is exchange rate stability. Foreign exchange volatility is a measure of currency stability. This precondition is to some extent in contrast with historical evidence that foreign exchange risk is pronounced in new EU members (Kočenda and Valachy, 2006). Finally, Kočenda and Poghosyan (2009) show that 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 we study. 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.

Soriano and Climent (2006) review the relevant volatility transmission literature: studies that aim at foreign exchange volatility transmission are less frequent than those covering equity markets. Studies of volatility transmission analyzing forex data are chiefly based on low-frequency data. Kearney and Patton (2000) employ a series of multivariate GARCH models on the members of the former European Monetary System (EMS) prior to their complete monetary unification and find that less volatile weekly data exhibit a significantly smaller tendency to transmit volatility compared to more volatile daily data. Hong (2001) pursues a different approach, finding 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). 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 and Wadhwani (1990), Cheung and Ng (1996) and Hong (2001) develop tests of spillover effects based on a residual cross-correlation function. Finally, Diebold and 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 one can learn much 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). A limited number of recent studies make use of intraday or high-frequency data, hoping to address these and related issues. In an early study Baillie and Bollerslev (1991) examines volatility spillover effects in four foreign exchange spot rates (GBP, JPY, DEM, and CHF) vs. USD, recorded on an hourly basis, and fails to uncover the presence of volatility spillover effects between the currencies or across markets. Engle et al. (2009) study volatility spillovers based on a daily high-low range as a proxy for volatility. 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 volatility and, consequently, an improved inference about volatility transmission. To the best of our knowledge there are only two studies at the moment 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 and Melvin (2003) provide evidence of statistically significant intra- and inter-regional volatility spillovers in the DEM/USD and JPY/USD forex markets. In a more recent study, Cai et al. (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 forex mid-quotes. Our work directly contributes to this strand of literature by studying the CE region.

The contribution of our paper to the existing literature is a thorough study of volatility transmission among CE 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 et al. (2008). Within the model we formally test for volatility spillovers by running simple pairwise Granger causality tests. However, to properly assess the overall magnitude and dynamics 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. We therefore analyze the volatility spillovers by fitting our model separately for two sub-samples (2003–2007 and 2008–2009). Our empirical results document the existence of volatility spillovers between the CE foreign exchange markets. We find that each CE currency is characterized by a different volatility transmission pattern:

spillovers affecting the Czech koruna and Polish złoty were detected while the Hungarian forint seems irresponsive during the pre-crisis period (2003–2007). The picture changes quite dramatically when we look at the crisis period of 2008–2009: spillovers decrease in general but 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; direct evidence comes from the dramatic increase in the average correlation in the unconditional innovations of volatility transmission between pre-crisis and post-crisis periods. Thus, we find that in periods characterized by increased market uncertainty, the CE 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 set out our theoretical framework and modeling strategy, and derive the dynamic version of the volatility spillover index. We describe the data in Section 3 and report the empirical results in Section 4. Section 5 concludes the paper with a short discussion and suggestions for future research.

2. Methodology

Following the approach of Andersen et al. (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). We make no parametric assumptions regarding the respective laws of motion (Andersen et al., 2003).

A natural measure of variability in this model is the well-known quadratic variation 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 et al. (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, the method requires no parameter restrictions 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 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 performs remarkably well in reproducing the widely documented presence of the volatility of financial products.

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 et al., 2008), recent findings that a univariate HAR-GARCH model fits very well the realized variances of the CE exchange rates (Bubák and Žikeš, 2009) drives our motivation for generalizing the model with an MGARCH structure.

To model the dynamics of the conditional variance of the innovation process $\boldsymbol{\varepsilon}_t$ **,** we employ the DCC model of Engle (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 and Sheppard (2001) and Engle (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 and Tits (2001). We estimate the model efficiently in one step to obtain valid standard errors for the DCC estimates.[1]

It is easy to see that one can write the VHAR model as a VAR(22) with restricted parameters. We can therefore employ the index of Diebold and 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:

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

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

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

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

The optimal *h*-step ahead forecast is given by

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

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

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

so we can write

$$\boldsymbol{\Sigma}_{t+h|t} = \mathbf{A}_{t+h|t}^{(0)} \mathbf{A}_{t+h|t}^{(0)\prime} + \mathbf{A}_{t+h|t}^{(1)} \mathbf{A}_{t+h|t}^{(1)\prime} + \cdots + \mathbf{A}_{t+h|t}^{(h-1)} \mathbf{A}_{t+h|t}^{(h-1)\prime}.$$

[1] 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 and Sheppard, 2001) and hence are not fully efficient. In our estimation, we use the two-step estimation procedure to obtain accurate starting values for the one-step estimation. Note, however, that we perform both the one-step and the two-step estimations and the corresponding estimates are nearly identical.

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

$$\mathbf{S}_{t+h|t} = \frac{\sum_{l=0}^{h-1} \sum_{\substack{i,j=1 \\ i \neq j}}^{k} (a_{t+h|t}^{(l)}(i,j))^2}{\sum_{l=0}^{h-1} \operatorname{tr}(\mathbf{A}_{t+h|t}^{(l)} \mathbf{A}_{t+h|t}^{(l)\prime})}.$$

In the above definition $a_{t+h|t}^{(l)}(i,j)$ is a typical element of $\mathbf{A}_{t+h|t}^{(l)}$. 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.

3. Data

We base our analysis 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 złoty (EUR/PLN). The data on exchange rate quotes cover a period of 6.5 years between January 3, 2003 and June 30, 2009. The data for the three CE currency pairs come from Olsen Financial Technologies (Olsen). The data for the EUR/USD exchange rate come 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. Finally, for the purpose of our analysis we distinguish two periods of data: from January 2, 2003 to December 30, 2007 (Period 1) and from January 2, 2008 to June 30, 2009 (Period 2). As we show later, the exchange rate volatility series exhibit different behavior across the two sample periods.

The EBS Spot Dealing system is currently the largest and most liquid platform for trading 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 et al. (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. Then, (ii) 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. Finally, (iii) 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 et al., 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, which are common to all four currency pairs, as well as December 26 (Christmas) and Easter Monday, which are common only to the CE 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.[2] Finally, following Andersen et al. (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 CE and EUR/USD currency pairs. First, as shown in Bubák and Žikeš (2009), the CE 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 et al. (2008). Second, we identify no microstructure noise in the 5-minute intraday returns of the EUR/USD exchange rate. 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, although the CE 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

[2] 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.

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. Figure 1 supplements 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 the equally significant yet mutually opposite developments on the CE and EUR/USD markets. Indeed, following a prolonged depreciation of the Czech and Polish currencies in the period before the start of the financial crisis,[3] the critical events of August 2008 initially lead to sharp depreciations of all three CE currencies while later, during the first months of 2009, all the currencies appreciated in unison. The US dollar, on the other hand, experienced nearly the opposite development pattern over the same period.

A specific 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 and 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 at the 1% significance level for EUR/PLN and at the 5% level 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.

Figure 2 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.

[3] The Hungarian forint followed a different development than other the two CE currencies. The main reason was that, until February 2008, the Hungarian Central bank managed the forint’s fluctuations with respect to the euro within a ±15 % band.

Aside from the influence of major events, volatility increases for those countries with troubled development of their financial sector (eg. Hungary). We note in Section 1 that the sub-prime crisis of 2008 marked a structural break in the behavior of the exchange rates under research; we give a formal account presently, in Section 5.1. In Figure 3 we show that the presence of a structural break at the beginning of 2008 affected the persistence of the autocorrelation function of the realized variance (RV). The plotted ACF of log(RV) during Period 1 (2003–2007) exhibit slow decays consistent with a very persistent, long-memory type of dynamics. On the contrary, Period 2 (2008–2009) has very low persistence of the ACF. We conjecture that differences in patterns between the two periods should be attributed to differences in the volatility transmissions that we present in Section 4. Finally, in several instances the (relatively) large spikes in RV during Period 1 are related to the underlying (economic) events and increased uncertainty in the relevant forex markets. Because of our thorough robustness check, we are confident that several big spikes in the first sub-sample do not affect the results of the volatility transmission analysis presented in Section 4.[4]

4. Empirical results

After the earliest attempts to study intraday volatility patterns in foreign exchange markets, Dacorogna et al. (1993) applies time-invariant polynomial approximations in order to study activity in different geographical regions of the market across the trading day and develops a relatively simple geographical model of the changing and sometimes overlapping market presence of geographical components. Following the spirit of this approach we briefly review the dynamics of the around-the-clock trading activity on the forex markets before presenting our results. This will help us understand the specific intraday pattern that characterizes the volatility of CE 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 CE foreign exchange markets.

[4] For the robustness check we select three spikes in the case of EUR/CZK, two spikes in the case of EUR/HUF, three spikes in the case of EUR/PLN, and one spike in the case of EUR/USD. For each selected spike we substitute its value with the average of the realized volatility of the previous twenty days. We then estimate the volatility transmission system based on this new adjusted series of realized volatilities. The results are nearly the same as those obtained with the original series with spikes. More importantly, the volatility transmission pattern does not change and the relevant coefficients remain both quantitatively and qualitatively comparable to those obtained with the original series.

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, 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 CE 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: we compute the variance for each of the 48 intraday 30-minute intervals and then average them over the whole sample and smooth them by a cubic spline.

We first discuss the plots corresponding to the CE 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 EUR/USD 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 CE markets are typically associated with the UK bank holidays, with a limited relation to the holidays relevant to a given CE country. This confirms the dominance of the London market.

4.1. Sample periods and Granger causality tests

We analyze 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 therefore, we perform all tests and estimations separately for the two sub-samples. Although reported for the exchange rate currency pairs, we carry out the causality tests as truly multivariate tests based on the full multivariate system that includes all four currencies.

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 złoty. 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 regional currencies.

Turning our attention to the EUR/HUF equation, we observe that the Hungarian forint is largely weakly exogenous as the tests indicate only marginally significant (at 10%) Granger causality running from CZK (in Period 1) and PLN (in Period 2) towards HUF. We conjecture that this result is due to the fact that until March 2008 the Hungarian Central Bank managed the forint under a ±15 % fluctuation band with respect to the euro and generally expressed heightened concerns about the forint exchange rate. 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.

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 CE 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. One should then look for a potential source of the increased volatility during Period 2 more in local autonomous market uncertainty rather than spillovers.

4.2. Volatility transmission model

Following from the discussion of 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}.[5] 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. We then investigate whether this part of the EUR/USD daily volatility spills over into the next day's volatilities of the CE exchange rates.

We report the estimation results for the volatility transmission model in Table 3. We present the estimates for the two sub-samples separately and to save space only report the restricted

[5] 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.

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 short-term and long-term variance components of EUR/HUF ($\beta_{1,HU}$ and $\beta_{22,HU}$, respectively) and the long-term variance component of the EUR/USD exchange rate, $\beta_{22,US}$ affect the current volatility of EUR/CZK. 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 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 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 the 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 above results are intuitively in line with those of Chuluun et al. (2011), who document cross-currency and temporal variations in random walk behavior in the exchange rates of numerous floating currencies. Our finding that volatility spillovers affect considerably the volatility of the Czech and Polish currencies correlates with the results of Chuluun et al. (2011) that both currencies exhibit very similar and small deviations from a random walk. The managed regime of the Hungarian currency and its spillover immunity fit the pattern quite well.

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 CE exchange rates, while we find the latter dummy highly statistically significant in all but one case (HUF). These results are in line with the discussion above 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.

We report the results for Period 2 (January 2003 to June 2009) 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 domestic holidays 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, we find the long-term own-variance component to have no effect on the present volatility of EUR/USD.[6]

Different sets of results for both pre- and post-crisis periods may stem from the potential different set of sentiment drivers during the crisis that the CE countries tried to cope with. These countries are heavily dependent on international trade, chiefly with the rest of the EU, and they experienced deep declines in exports. A dramatic deterioration of their public finances involved the emergency issues of government bonds besides other steps and interventions similar to those that other countries adopted in reaction to global financial crisis (Moshirian, 2011). Further, as monetary policy became less effective during the crisis both factors and especially their

[6] We perform a robustness check to assess spillover effects when weekly realized variance with a smaller noise level is used as a dependent variable. We find that the results are not materially different and conclude that the lack of spillover effect does not seem to be due to higher noisy estimates of the daily RV of the four currencies (we do not present the results but they are readily available upon request). The short-term variance component (the first lag of the logarithmic realized variance) carries very low explanatory power in predicting the weekly RV as it remains generally non-significant across the equations. In the volatility transmission pattern during the post-crisis Period 2 the general lack of variance components of other CE currencies becomes evident for all CE currencies. The long-term variance component of USD becomes significant in the case of the Czech koruna and the Hungarian forint, as well as the USD itself.

magnitude would be enough to overwhelm CE markets with an isolationist sentiment and decreased effect of spillovers from neighboring markets.

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.[7] 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 (available upon request) reveals no obvious dependence patterns as the series appears to be *i.i.d*. 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 5 shows the correlations implied by the DCC model as estimated for Period 1. (Recall that we fit a CCC model to Period 2.) We observe time-varying and 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.[8] The intuition behind this result points to a low degree of integration among the CE forex markets that is also fully in line with the low synchronization of the CE capital markets documented by Égert and Kočenda (2011).

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[7] We obtain coefficients from the estimation of the variance of the realized variance and not of the exchange rate per se. The absence of significant β coefficients (GARCH effect) for the USD in Period 1 and for the CZK in Period 2 suggest that the variance structure of the realized variance can be in these two relevant instances described by a (simple) ARCH model.

[8] Li (2011) shows that correlations between the exchange rates of five inflation-targeting (IT) countries are dynamic and time-varying. The three CE countries in our sample are also inflation targeters but the result of Li (2011) may not necessarily be unique to IT countries. Further, in terms of pairwise analysis we perform a lead-lag correlation analysis with the size of the time displacement of the daily realized variance (RV) from 5 minutes up to the start of the trading day (7:00h GMT). The following patterns emerge: 1. The decrease of the displacement size to 5 minutes is associated with an increase in correlation, eg. the lead-lag link is more dependent. 2. Lead-lag correlations are low (0.1–0.3) but quite persistent during Period 1. 3. Lead-lag correlations are high (0.4–0.7) but less persistent and exhibit decay in Period 2. We do not report the detailed results but they are available upon request.

4.3. Spillover index

Figure 6 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. We also note that with respect to the difference between the pre- and post-crisis periods, the average correlation in the unconditional innovations of the volatility transmission model increases by about 70 percent, from 0.19 during the pre-crisis period to 0.33 during the post-crisis period. 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.

5. Conclusions

In this paper, we analyze the nature and dynamics of volatility spillovers between CE 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 an exchange rate's history as well as the volatilities of other exchange rates of the system realized over different time horizons drive the realized volatility of the given exchange rate. Given the multivariate framework, the model helps us study both the 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 CE foreign exchange markets on an intraday basis. We find that each CE currency has a different volatility transmission pattern. During the pre-2008 period, the histories of the Czech and Polish currencies and both the short- and long-term volatility components of the Hungarian currency as well as the long-term volatility component of EUR/USD affect the volatilities of the Czech and Polish currencies. In contrast, EUR/HUF seems generally irresponsive to any foreign component. Our finding that volatility spillovers have a greater effect on the volatility of the Czech and Polish currencies correlates with the fact that both currencies exhibit very similar and small deviations from a random walk. This contrasts with the managed regime of the Hungarian currency and its volatility being irresponsive to spillovers. During the post-2008 period our results show that volatility increased in general but the volatilities of all currencies reflect chiefly their own history. This lack of effect from neighboring markets might be a sign of isolationist sentiment on the forex markets during the global crisis. Further, using a dynamic version of the Diebold-Yilmaz spillover index we find that 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 financial sector development (e.g. Hungary). Finally, a general difference in the pre- and post-crisis patterns is an increase in the strength of the short-term relation, which seems to indicate a generally faster reaction of the market to volatility dynamics, especially in case of the CZK, PLN, and USD.

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 et al. (2009). Further, the synthesis of our findings is also relevant from the perspective of research on investment strategies as Jotikasthira et al. (2010) show that all of the three countries under research are attractive investment destinations. 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 multivariate Granger causality 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 $\beta_1 = \ldots = \beta_{22} = 0$ (the corresponding *p*-values of the *F*-statistics are shown in parentheses). 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* (0.009)	0.780 (0.505)	3.355* (0.010)	–	0.640 (0.590)	1.554 (0.200)	2.414* (0.049)
HUF	2.234^c (0.083)	–	1.419 (0.236)	0.525 (0.718)	0.198 (0.898)	–	2.476^c (0.061)	0.521 (0.720)
PLN	0.191 (0.903)	6.785* (0.000)	–	2.709* (0.029)	1.436 (0.232)	1.734 (0.160)	–	0.774 (0.543)
USD	4.159* (0.006)	1.035 (0.376)	0.536 (0.658)	–	1.217 (0.303)	1.274 (0.283)	2.069 (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		-0.023				
	(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)	(1.409)	(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)

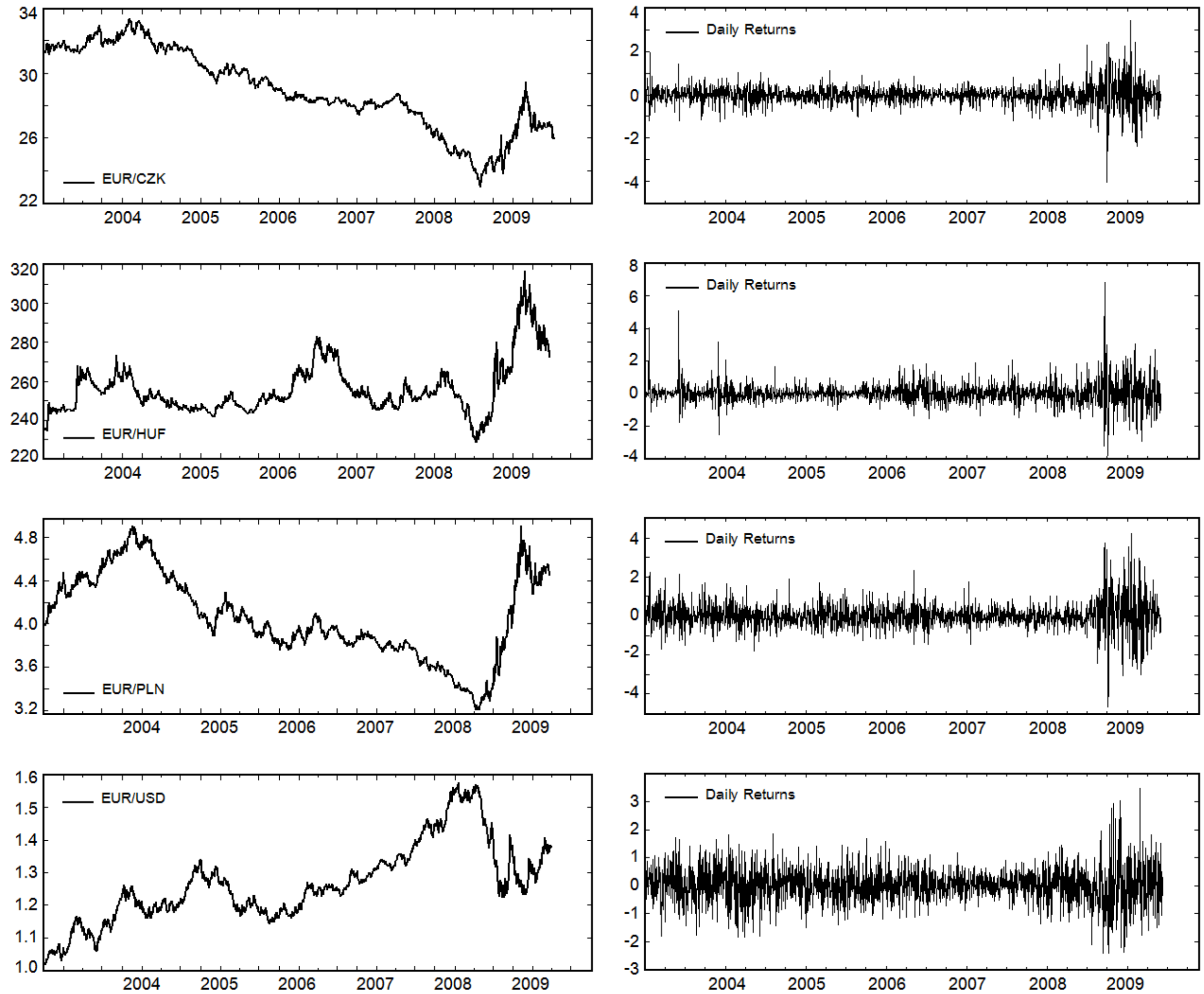


Fig. 1 Plots of daily spot rates (left) and daily returns (right) for the case of EUR/CZK (first row), EUR/HUF (second row), EUR/PLN (third row) and EUR/USD (last row) exchange rates. The sample runs from January 3, 2003 to June 30, 2009.

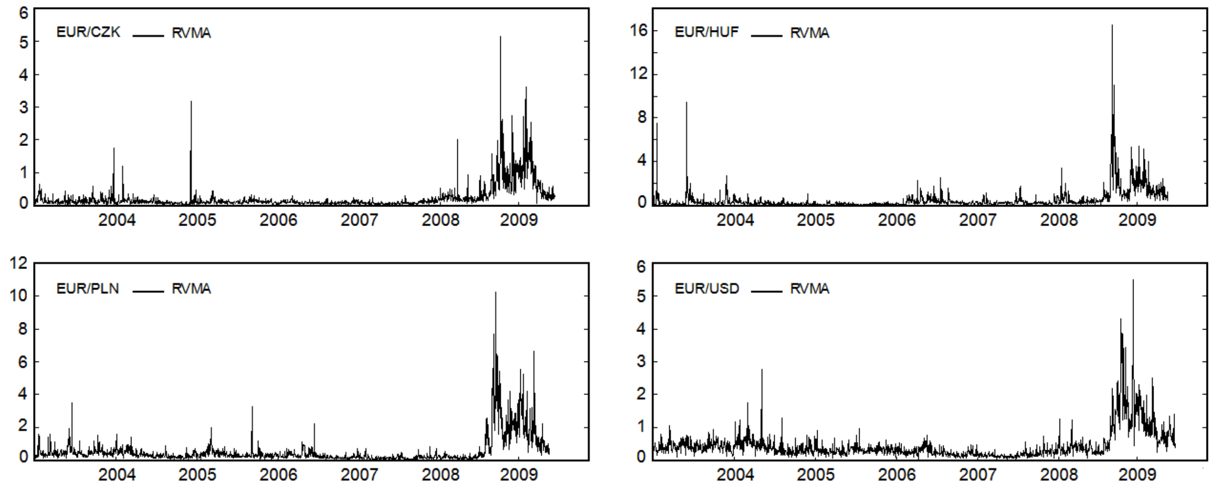
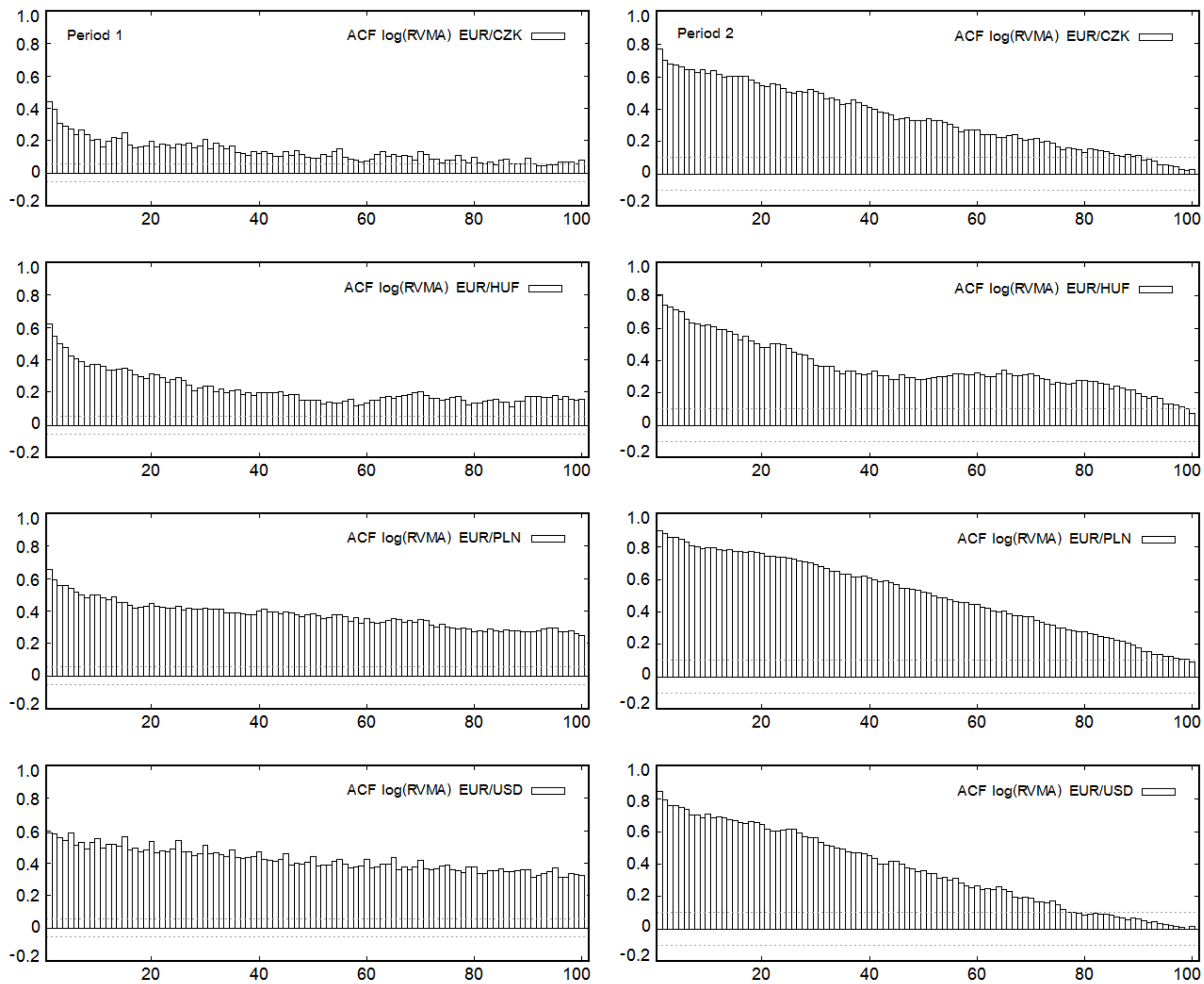


Fig. 2 Plots of daily realized volatility (*RV*) for the case of EUR/CZK (first row, left), EUR/HUF (second row, right), EUR/PLN (second row, left) and EUR/USD (second row, right) exchange rates. The sample runs from January 3, 2003 to June 30, 2009.



Period 1. **Period 2.**

Fig. 3 The ACF plots of log(RV) for the case of EUR/CZK (first row), EUR/HUF (second row), EUR/PLN (third row) and EUR/USD (last row) exchange rates, as estimated for Period 1 (January 2, 2003 to December 30, 2007) in the left column, and for Period 2 (January 2, 2008 to June 30, 2009) in the right column.

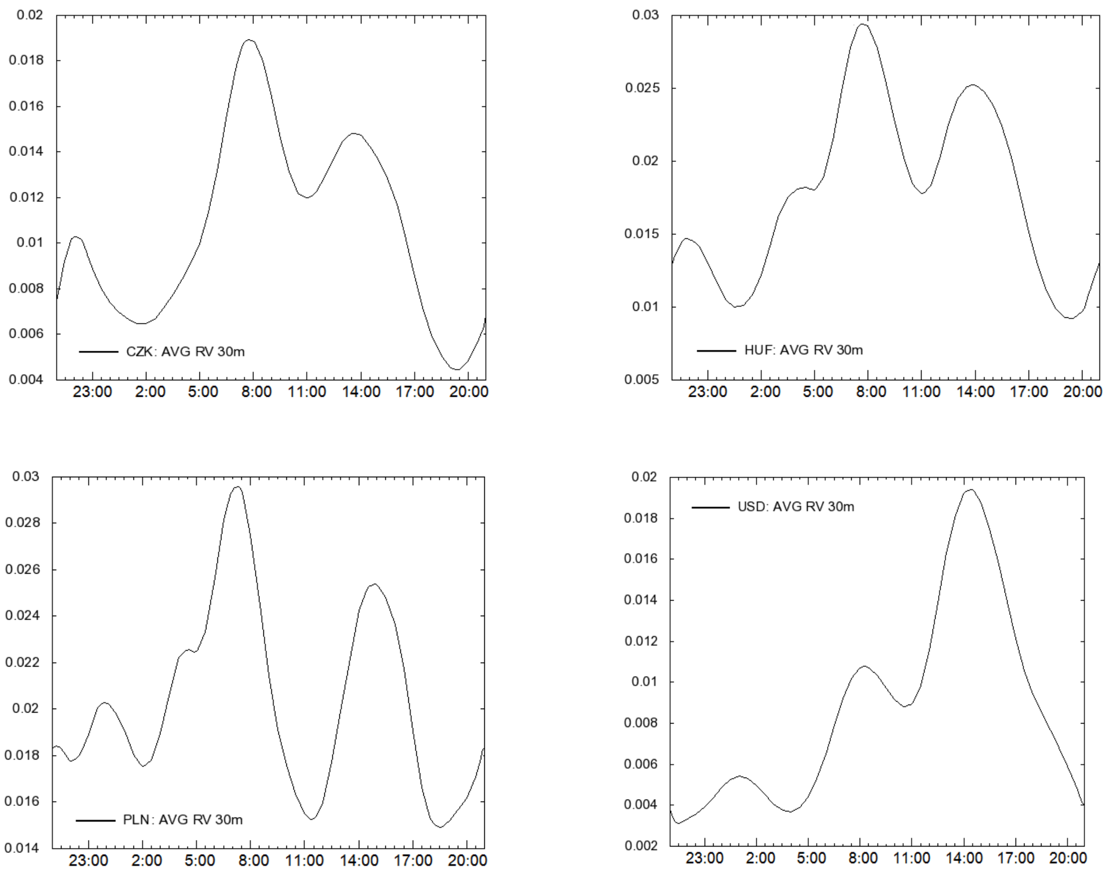


Fig. 4 An intraday evolution of realized volatility for EUR/CZK (top left), EUR/HUF (top right), EUR/PLN (bottom left) and EUR/USD (bottom right) exchange rates. The realized volatility is computed over 30-minute intraday intervals starting at 21:00h on day (*t*–1) and ending at 21:00h on day (*t*) and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

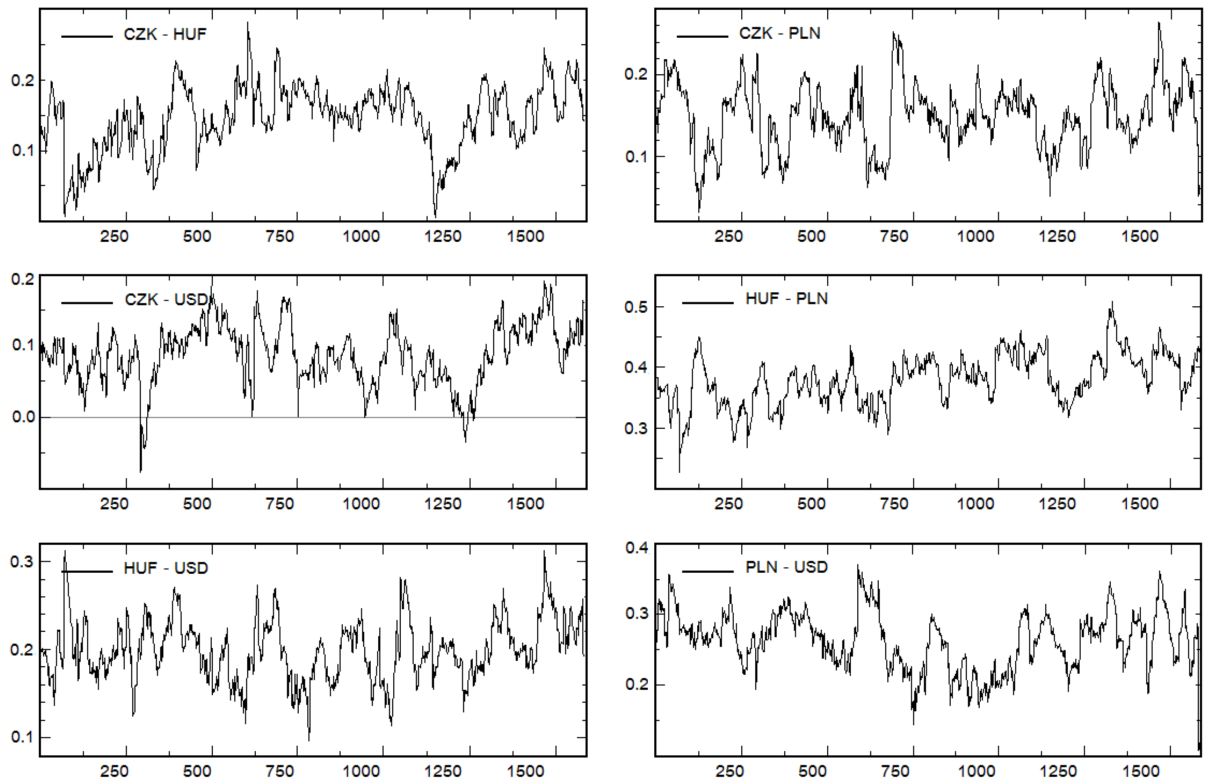


Fig. 5 Plots of conditional correlations as implied by the DCC-MGARCH model estimated for Period 1 (January 2, 2003 to December 30, 2007) for the four exchange rate currency pairs analyzed in the study.

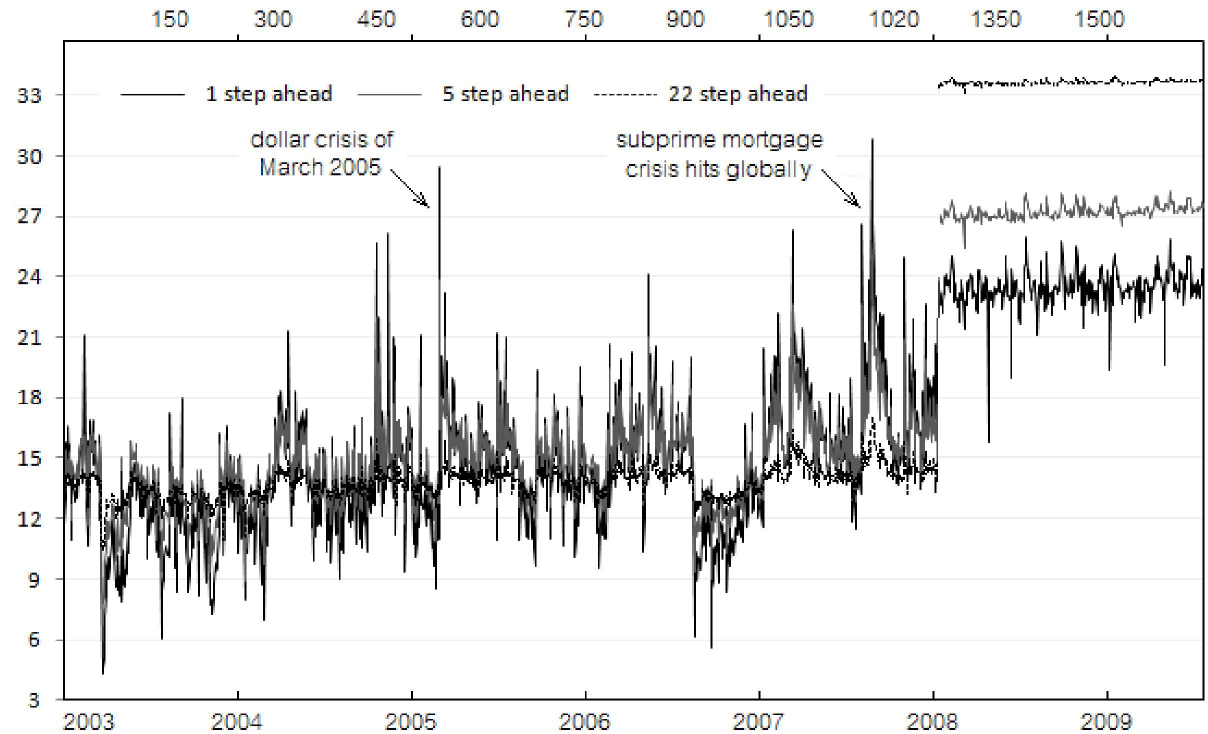


Fig. 6 The volatility spillover plot. At any point in time, the volatility spillover index is defined as the sum of all contributions to the forecast error variances of currency pair *i* generated by innovations to currency pair *j*, added across all *i*'s. The top of the figure includes the number of observations.

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