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Bidirectional Volatility Spillover Effect between the Exchange Rate and Stocks in the Presence of Structural Breaks in Selected Eastern European Economies

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Abstract
This paper investigates the second moment spillover effect between stock returns and exchange rate changes in both directions in four Eastern European emerging markets, assuming the presence of multiple structural breaks. The data sample consists of daily observations and the methodology is based on a two-step symmetric/asymmetric fractionally integrated generalized autoregressive conditional heteroskedasticity approach, with a rolling technique and structural breaks integration. The results indicate that the spillover effect has a much greater impact when spillover is from the exchange rate market toward the stock market than in the opposite case and it is time-varying. The inclusion of structural breaks in the model implies that the volatility spillover effect might be biased in stock markets. The applied models suggest that volatility persistence is overestimated in all asset markets if sudden changes are not recognized in the models.

1. Introduction

Financial markets have become more integrated in recent decades, according to the findings of Babecky *et al.* (2013), Horvath and Petrovski (2013) and Horvath and Poldauf (2012). After the initiation of the transition process, many Eastern European countries (EECs) liberalized their financial markets, which was followed by a substantial increase in the volume of international transactions in both securities and currencies. These countries have experienced fairly large capital inflows in the past two decades due to robust economic growth, gradual disinflation and the liberalization of capital accounts, as argued by Josifidis *et al.* (2009). In such circumstances, relatively large volumes of capital influx followed by the growing participation of international investors in equity end exchange markets affected the demand/supply of domestic stocks as well as domestic currencies. This eventually led to some extent to mutual intertwining between equity prices and exchange rate dynamics (Kanas, 2000).

Many international investors and portfolio managers try to understand the mutual dependencies between the two major financial assets—foreign exchange and stocks, since investment in a national stock market involves exposure to exchange rate risk. Most empirical studies explain the linkage between stock and foreign exchange markets using first moments in their analysis, while less attention has been paid to the volatility interrelationships between these markets. Taking into account that any change in variances in national stock markets caused by exchange rate fluctuations makes it more difficult for investors to select an optimal investment strategy, good comprehension of the second moment spillover effect is important for investors. Besides that, the common characteristic of daily asset return series, observed in relatively long-range periods, is susceptibility to multiple structural changes, which could lead to spurious parameter measures and erroneous conclusions. Henry (2000) and Chaudhuri and Wu (2003) asserted that structural shifts can cause incorrect inferences in market efficiency analysis of international stock markets. Particularly, Ewing and Malik (2005), Huang (2012) and Jung and Maderitsch (2014) found evidence that the volatility spillover effect could be heavily biased if structural jumps are not recognized in the models. However, Mikosch and Starica (2004), Hillebrand (2005) and Kramer and Azamo (2007) contended that volatility persistence might be overestimated if deterministic regime shifts are neglected, with the tendency toward an integrated generalized autoregressive conditional heteroskedasticity (IGARCH) process.

This paper has several objectives. The first hypothesis states that the second moment spillover effect between stocks and the exchange rate exists in both directions. The second hypothesis is that this effect is not objective if multiple structural breaks are not inserted into the model, which is tested by applying the fractionally integrated GARCH (FIGARCH) methodology. We tested the assertion that long-range persistence in variance exists if structural breaks are disregarded in the GARCH model. The modified iterative cumulative sum of squares (ICSS) algorithm by Sansó *et al.* (2004) was applied to detect structural breaks in the unconditional variance. The analysis was focused on four transition EECs, namely the Czech Republic, Hungary, Poland and Russia, within a time span of thirteen years, from 2002 to the end of 2014. Some of those countries pursued a *de facto* flexible exchange rate during this period (the Czech Republic and Poland), while Hungary had a fixed regime with wide bands and Russia had tight management until 2008 and greater exchange rate flexibility afterwards. Yet, we also analyzed developed US market, which served as a benchmark.

The contribution of this paper could be referred as two-fold. Firstly, to the best of our knowledge, none of the existing papers gauges the volatility spillover effect in the presence of structural breaks between these two asset markets in this group of countries. Secondly, very few existing academic papers have analyzed EECs assuming the long memory persistence and presence of structural breaks in the stock markets and exchange rate markets. The awareness of the presence of long memory in volatility starts to play an important role, since it implies that past data trends can be used to predict future returns, which is of paramount importance for participating investors. Besides that, the presence of structural breaks tends to increase long memory persistence in variance. For instance, Kasman *et al.* (2009) envisaged the long memory in eight Eastern European stock markets, but neglected possible structural breaks bias. On the other hand, Wang and Moore (2009) scrutinized five Central European stock markets assuming the presence of structural breaks, but without fractionally integrated persistence in the variance. As far as we know, none of the papers analyzes long memory persistence using the FIGARCH methodology in the Eastern European asset markets, while also taking into account the presence of multiple structural breaks. Our study is aimed at filling these gaps in the literature.

The rest of the paper is organized as follows: Section 2 considers the extant theoretical literature. Section 3 describes the modified ICSS method of structural breaks detection and several autoregressive-moving-average (ARMA) FIGARCH approaches. Section 4 presents the dataset analysis and Section 5 portrays structural breaks and detection thereof. Section 6 is reserved for research findings and Section 7 concludes the paper.

2. Theoretical Background and Related Studies

The existence of an interrelationship between stocks and the exchange rate is well known in the international financial literature. Economic theory proposes two main approaches that address this linkage: the traditional or "flow-oriented" model and the portfolio-balance approach or "stock-oriented model". The flow-oriented approach finds the linkage via the international trade balance. Exchange rate movements (depreciation/appreciation) affect the competitiveness of domestic/foreign goods, which consequently reflects on the balance of trade position. The growth of real output influences the current and future cash flows of domestic companies, especially those that are export-oriented, making their stock prices rise. This indirect linkage occurs via the balance of payments, supporting the positive correlation between these two assets. On the other hand, the portfolio-balance approach is based on the demand and supply of financial assets. Increased demand for domestic stocks could cause greater need for the domestic currency, which eventually leads to its appreciation. Conversely, if the exchange rate appreciates/depreciates due to some external shocks, it would increase/decrease demand of domestic stocks and cause their value to rise/fall. The portfolio-balance model is in line with the direct relationship between these two variables.

Generally, the vast majority of empirical research on the relationship between exchange rates and stock prices is focused primarily on the first moment regression, i.e. the price spillover effect, neglecting second moment influences. Additionally, most studies, which address the variance spillover effect, predominantly focus on developed countries. For instance, the impact of second moment spillover between stock and foreign exchange markets was investigated in the case of six developed countries (the US, the UK, Japan, Germany, France and Canada) by Kanas (2000). He found a significant spillover effect from stock returns to exchange rate changes for all countries except Germany by utilizing daily closing stock prices. However, spillovers from exchange rate changes toward stock returns have not been found in any country. Aloui (2007) also investigated the dynamics of price and volatility spillovers in developed countries, observing major European markets in the periods prior to and following adoption of the euro. His research found significant volatility spillovers from stock markets to exchange rate markets for most of the countries in both periods. The opposite direction was found in the period following adoption of the euro in three out of five countries. No volatility spillovers from the exchange rate to stocks were found in the pre-euro period. Mun (2007) investigated the US market and the results indicated that higher foreign exchange rate variability mostly increases local stock market volatility, but decreases the volatility of the US stock market. The study by Jayasinghe and Tsui (2008) investigated the link between stocks and the exchange rate in Japan. They contended that there is conditional volatility of stock returns in six industrial sectors that are positively exposed to exchange rate changes, providing evidence that volatility in these sectors increases with an increase in the volatility of the exchange rate. Grobys (2015), using daily data, examined the volatility spillovers between the foreign exchange rate markets of three of the United States' major trading partners (Canada, the EU and Japan) and the US stock market. The findings suggest that the level of volatility spillover effects is high only in periods preceding economic turbulence. Conversely, if the economy is stable, volatility spillover effects are virtually non-existent.

Andreou *et al.* (2013) investigated bidirectional linkages between the stock and foreign exchange markets in twelve emerging markets and found a significant spillover effect in both directions in all selected economies except Colombia. The research of Sensoy and Sobaci (2014), conducted on daily data, reported a dynamic relationship between the exchange rate, interest rate and the stock market in Turkey. They concluded that abrupt changes in the correlation levels (caused by volatility shocks) between the stock and exchange rate markets are valid only in the short run, meaning that investors do not need to be concerned about long-run contagion effects. In another study, Kasman *et al.* (2011), employing daily closing stock prices, claimed that interest rate and exchange rate volatilities are the major determinants of the volatility of banks' stock returns. Utilizing both daily and weekly data, Bonga-Bonga and Hoveni (2013) assessed the extent of volatility spillovers between the equity market and the foreign exchange market in the emerging South African market. Using a GARCH model, they discovered that volatility spillovers were present in the direction from the equity market to the foreign exchange market, but not vice versa. Using weekly data, Walid *et al.* (2011) investigated the dynamic linkage between stock price volatility and exchange rate changes in four emerging countries. They reported that stock price volatility responds asymmetrically to events in the foreign exchange market and its reaction depends on the regime of the conditional mean and conditional variance of stock returns. Zhao (2010) showed that a bi-directional volatility spillover effect exists between the Renminbi (RMB) real effective exchange rate and stock prices in China. One of the rare papers that addressed Eastern Europe countries was published by Fedorova and Saleem (2010), who utilized weekly data and a bivariate GARCH- BEKK (Baba, Engle, Kraft and Kroner) model in four countries: Poland, Hungary, Russia and the Czech Republic. The evidence indicated that volatility spillover happened in a unidirectional way, from exchange rate markets to stock markets, in all the countries. However, in the case of the opposite direction, the exception was the Czech Republic, where the exchange rate market is also found to be affected by the stock market.

3. Methodology

3.1 Test of Structural Break Detection in the Variance

The existence of structural breaks is a common problem in daily frequent asset series. This is especially true for less resistant emerging markets. From an arbitrary point of view, it can be argued that all selected asset markets suffered a tremendous impact when the shock of the globe financial crisis spilled over. Since our samples cover a relatively large period, including the outbreak of the global crisis, the conjecture is that the data series probably suffer from multiple structural shifts. Earlier in the text, it is stated that some studies found evidence that structural breaks could cause volatility spillover bias and higher volatility persistence. Also, Marcelo *et al.* (2008) claimed that an asymmetric effect in the GARCH framework could be biased if sudden shifts were not taken into account. This is another hypothesis to be tested. In order to detect structural breaks, we employed a modified version of the iterative cumulative sum of squares (ICSS) algorithm by Inclan and Tiao (1994) (hereinafter referred to as "IT").

The underlying ICSS algorithm assumes that unconditional variance of a time series is stationary over an initial period of time, until a sudden jump occurs. The variance then reverts to stationary until another shock happens on the market. This process is reiterated over time, producing a time series of observations with an unknown number of breaks in the variance. Assuming an independent time series (τ_t) with zero mean and variance σ_t^2, the IT statistic is as follows:

$$IT = \sup_k \left| \left(T/2 \right)^{0.5} D_k \right| \tag{1}$$

where D_k is given by $D_K = \left(C_k / C_T \right) - K/T$. The cumulative sum of squares from the first observation to the k-th point in time is expressed according to the equation $C_k = \sum_{t=1}^{k} \tau_t^2$, where $k = 1,...,T$. C_T is the sum of squared residuals from the whole sample period. If sudden changes in the variance do not occur, the D_k will oscillate around zero. Conversely, if there is at least one jump in the variance of the series, the D_k statistic varies from zero.

However, the IT procedure assumes an *i.i.d.* process, which is a highly unlikely characteristic for financial series, where a dependent GARCH process is present. The studies of de Pooter and van Dijk (2004) and Sans'o *et al.* (2004) showed that the IT procedure can be significantly oversized due to the presence of heavy tails, where extreme values are interpreted as change points, even though they should be classified as outliers. Therefore, we followed Sansó *et al.* (2004), who suggested a new test, a modified ICSS, which explicitly considers the fourth moment properties of the time series. In accordance with Sansó *et al.* (2004), we utilize a non-parametric IT adjustment based on the Bartlett kernel, which is specified as follows:

$$AIT = \sup_k \left| T^{-0.5} G_k \right| \tag{2}$$

where

$$G_k = \hat{\lambda}^{-0.5} \left[C_k - (k/T) C_T \right]; \hat{\lambda} = \hat{\gamma}_0 + 2 \sum_{l=1}^{m} \left[1 - l(m+1)^{-1} \right] \hat{\gamma}_l ; \hat{\gamma}_l =$$

$$= T^{-1} \sum_{t=l+1}^{T} \left(\tau_t^2 - \hat{\sigma}^2 \right) \left(\tau_{t-1}^2 - \hat{\sigma}^2 \right)$$

$$\hat{\sigma}^2 = T^{-1} C_T$$

According to the procedure of Newey and West (1994), we set the lag truncation parameter $m = 0.75 T^{1/3}$.

By using the modified ICSS algorithm, we recognize multiple structural shifts in the models' conditional variances via dummy variables. Every dummy variable is defined as unity from a structural break onwards and zero otherwise.

3.2 Two-Step Approach via Symmetric and Asymmetric FIGARCH Models

A common characteristic of daily asset returns is that their volatility exhibits very persistent autocorrelation with long memory or hyperbolic decay, as claimed by Baillie *et al.* (2007). The concept of long memory is related to a high degree of persistence in the observed data, which implies that time-distant observations are still strongly correlated and decay at a slow rate. Long memory persistence, which implies that distinct data observations could be associated with current series realization, stands against the efficient market hypothesis (EMH) postulation. Assuming the presence of long memory in the conditional volatility of selected asset series, we utilize the FIGARCH framework proposed by Baillie *et al.* (1996).

Additionally, in order to evaluate the bidirectional volatility spillover effect, a two-step FIGARCH approach was utilized. Firstly, we determine the best ARMA(m,n) model for every asset return series and then we generate and innovation series from the optimal ARMA(m,n) specification. In the second step, such acquired volatility shocks of the stock returns and exchange rate changes are installed in the conditional volatility equation of the optimal symmetric (asymmetric) FIGARCH in the corresponding opposite markets. This procedure allows us to assess the extent to which shocks in one market affect the conditional volatility in another market. The mean equations of the stock returns and exchange rates in the first step have the following form:

$$r_{m,t} = C_r + \sum_{i=0}^{p} \Omega_i r_{m,t-i} + \sum_{j=0}^{q} \Phi_j \varepsilon_{m,t-j} \; ; \; \varepsilon_{m,t} = z_{m,t}\sigma_{m,t} \qquad z_{m,t} \sim iid \tag{3}$$

$$e_{n,t} = C_e + \sum_{i=0}^{p} \Theta_i e_{n,t-i} + \sum_{j=0}^{q} \Psi_j \xi_{n,t-j} \; ; \; \xi_{n,t} = \overline{z}_{n,t}\sigma_{n,t} \qquad \overline{z}_{n,t} \sim iid \tag{4}$$

where $r_{i,t} = 100 \times \log\left(P_{i,t} / P_{i,t-1}\right)$ and $e_{i,t} = 100 \times \log\left(FX_{i,t} / FX_{i,t-1}\right)$; $r_{i,t}$ is the stock market return and $P_{i,t}$ is the stock closing price for national stock index (*m*) at time (*t*). $e_{i,t}$ is the exchange rate change and foreign exchange (*FX*) is the nominal exchange rate of the particular currency (*n*) compared to the euro at time (t). ε_t and ξ_t are independently and identically distributed error terms of various stocks and exchange rates, which were tested to determine what form of continuous probability distributions the residuals follow. Since residual distributions of selected daily frequent asset returns tend to report asymmetry and leptokurtosis, we considered the standard Student-t and skewed Student-t distributions.

The spillover impact was tested in both directions, from stock prices to exchange rate changes and vice versa. Using the best fitting symmetric (asymmetric) FIGARCH model, the volatility spillover effects were evaluated by adding squared innovation terms (ε^2 and ξ^2) obtained from equations (3) and (4) in the first step into the corresponding conditional variance equation. Only the contemporaneous innovation term was employed in the conditional variance equation because innovation lags proved to have a lower spillover effect. In order to find best fitting model as well as to check for the presence of asymmetries in the conditional volatility of the selected series, we estimated every asset series with several symmetric (asymmetric) FIGARCH specifications, namely fractionally integrated GARCH (FIGARCH), fractionally integrated asymmetric power ARCH (FIAPARCH), fractionally integrated exponential GARCH (FIEGARCH) and hyperbolic GARCH (HYGARCH). All parameters in the various FIGARCH models were estimated with the quasi-maximum likelihood procedure. Since we tried to evaluate the spillover effect under the influence of structural breaks, all the following conditional variance equations were presented with embedded exogenous dummy variables, which accounts for several structural breaks.

The general specification of the FIGARCH model introduced by Baillie *et al.* (1996) uses the fractional differencing operator $\left(1-L\right)^{d}$ in the IGARCH process, which constrains the roots $\left[1-\alpha\left(L\right)-\beta\left(L\right)\right]$ and $\left[1-\beta\left(L\right)\right]$ of ordinary the GARCH(p,q) process to lying outside the unit circle. The symbol d denotes the fractionally differencing parameter measuring the persistence of shocks to the conditional variance. The FIGARCH(p,d,q) model allows an intermediate range of persistence meaning that the d parameter lies within: $0 < d < 1$. In other words, FIGARCH envelops the other GARCH-type models, meaning that it is equivalent to the ordinary GARCH process when $d = 0$ and integrated GARCH when $d = 1$. Equations (5) and (6) respectively present the FIGARCH(p,d,q) specification of stock returns and exchange rate changes with respect to the exogenous spillover parameter and dummy variables.

$$\sigma^2_{(r),t} = \omega + \beta(L)\sigma^2_{(r),t} + \left(1-\beta(L)-\alpha(L)(1-L)^d\right)\varepsilon_t^2 + \varphi\xi_t^2 + \sum_{j=0}^{k}\varpi_j DUM_j \tag{5}$$

$$\sigma^2_{(e),t} = \omega + \beta(L)\sigma^2_{(e),t} + \left(1-\beta(L)-\alpha(L)(1-L)^d\right)\xi_t^2 + \varphi\varepsilon_t^2 + \sum_{j=0}^{k}\varpi_j DUM_j \tag{6}$$

where labels r and e stand for stock returns and exchange rate changes. The parameter φ in equations 5–13 measures the volatility spillover effect from currency shocks to the conditional variance of the stock returns and vice versa. The explanations of symbols r and e are uniform for all models below.

Depicting stock returns and exchange rate changes by equations (7) and (8) respectively, the fractionally integrated exponential GARCH (FIEGARCH) models developed by Bollerslev and Mikkelsen (1996) have the following forms:

$$\log\left(\sigma^2_{(r),t}\right) = \omega + \beta(L)^{-1}(1-L)^{-d}\left(1+\alpha(L)\right)g\left(z_{t-1}\right) + \varphi\log\xi_t^2 + \sum_{j=0}^{k}\varpi_j DUM_j \tag{7}$$

$$\log\left(\sigma^2_{(e),t}\right) = \omega + \beta(L)^{-1}(1-L)^{-d}\left(1+\alpha(L)\right)g\left(z_{t-1}\right) + \varphi\log\varepsilon_t^2 + \sum_{j=0}^{k}\varpi_j DUM_j \tag{8}$$

$$g\left(z_t\right) = \gamma_1 z_t + \gamma_2\left(\left|z_t\right| - E\left|z_t\right|\right) \tag{9}$$

where term $g\left(z_t\right)$ gauges the effect of the volatility response to "good news" and "bad news" in both equations (7 and 8). The asymmetric effect between equity returns and volatility is accommodated by the term $g\left(z_t\right)$, which is a function of both the magnitude and the sign of z_t, where parameter γ_1 captures the sign and γ_2 captures the magnitude of past errors.

Another variation of the general FIGARCH process is the fractionally integrated APARCH (FIAPARCH) of Tse (1998). Similar to the FIEGARCH model, the FIAPARCH also permits past shocks to have asymmetric effects on the conditional volatility. Regarding stock returns (10) and exchange rate changes (11), these models are specified as follows:

$$\sigma^{\delta}_{(r),t} = \omega + \left(1 - \left(1 - \beta(L)\right)^{-1} \alpha(L)(1-L)^d\right)\left(\left|\varepsilon_t\right| - \mu\varepsilon_t\right)^{\delta} + \varphi\xi_t^2 + \sum_{j=0}^{k} \varpi_j DUM_j \tag{10}$$

$$\sigma^{\delta}_{(e),t} = \omega + \left(1 - \left(1 - \beta(L)\right)^{-1} \alpha(L)(1-L)^d\right)\left(\left|\xi_t\right| - \mu\xi_t\right)^{\delta} + \varphi\varepsilon_t^2 + \sum_{j=0}^{k} \varpi_j DUM_j \tag{11}$$

where $-1 < \mu < 1$ and $\delta > 0$. Parameter μ is the leverage coefficient and when $\mu > 0$ negative shocks affect volatility more than positive shocks and vice versa. Parameter δ is the power term parameter and takes finite positive values.

Additionally, the HYGARCH model by Davidson (2004) was utilized. This model represents a generalization of the FIGARCH model with hyperbolic convergence rates. Davidson pointed out that the HYGARCH model allows both the existence of second moments and more flexibilities than the IGARCH and FIGARCH models. Assuming stock returns (12) and exchange rate changes (13), the HYGARCH specifications are structured as follows:

$$\sigma^2_{(r),t} = \omega + \beta(L)\sigma^2_{(r),t} + \left(1 - \beta(L) - \alpha(L)\left(1 + a(1-L)^d - 1\right)\right)\varepsilon_t^2 + \varphi\xi_t^2 + \sum_{j=0}^{k} \varpi_j DUM_j \tag{12}$$

$$\sigma^2_{(e),t} = \omega + \beta(L)\sigma^2_{(e),t} + \left(1 - \beta(L) - \alpha(L)\left(1 + a(1-L)^d - 1\right)\right)\xi_t^2 + \varphi\varepsilon_t^2 + \sum_{j=0}^{k} \varpi_j DUM_j \tag{13}$$

If a parameter takes the value of 1, the HYGARCH nests the FIGARCH. If $0 < a < 1$, the process is stationary; if $a > 1$, the process is nonstationary.

4. Dataset and Descriptive Statistics

The data set comprises the daily returns of the stock indices of four major post-communist Eastern European emerging economies: the Czech Republic (PX), Hungary (BUX), Poland (WIG) and Russia (RTS), as well as their corresponding currencies—koruna, forint, zloty and ruble. Additionally, we observed interdependence between the S&P 500 index and the US dollar and used it as a benchmark. Referring to Chkili *et al.* (2012), Grobys (2015) and Jayasinghe and Tsui (2008), we opted for daily frequency data. However, weekly data could also be an appropriate frequency for detecting spillovers,[1] as suggested by the studies of Mun (2007), Andreoua *et al.* (2013) and Fedorova and Saleem (2010). All asset returns are expressed as continuously compounded percentage rates of return. The data span ranges from January 2002[2] to December 2014 for all corresponding asset series, except for the Russian

[1] For our basic research we chose daily data, but we also conducted the same procedure on the weekly data as a robustness check. These results can be found in the online *Appendix*.

	Indices				Currencies			
	WIG	BUX	PX	RTS	Zloty	Forint	Koruna	Ruble
Panel A: Descriptive statistics of the data								
Mean	0.039	0.026	0.027	-0.053	0.004	0.007	-0.005	0.031
St. dev.	1.266	1.596	1.456	2.430	0.594	0.609	0.399	0.579
Skewness	-0.375	-0.102	-0.539	-0.361	0.297	0.671	0.414	0.770
Kurtosis	6.358	9.422	17.098	14.188	8.366	10.791	12.124	8.611
JB	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
LB(Q)	0.008	0.000	0.000	0.000	0.002	0.000	0.005	0.000
LB(Q^2)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: Unit root tests								
DF-GLS	-4.82	-11.14	-5.08	-36.12	-17.56	-8.77	-7.48	-8.54
KPSS	0.23	0.31	0.54	0.14	0.09	0.04	0.17	0.27

Notes: JB stands for the *p*-value of Jarque-Bera coefficients of normality, LB(Q) and LB(Q^2) tests denote the *p*-values of Ljung-Box Q-statistics for level and squared residuals for 20 lags. Assuming the absence of the trend, the 1% and 5% critical values for the DF-GLS test (modified Dickey-Fuller test with a generalized least squares rationale) with ten lags are -2.566 and -1.941, respectively. The 1% and 5% critical values for the KPSS (Kwiatkowski-Phillips-Schmidt-Shin) test are 0.739 and 0.463, respectively.

Source: Authors' calculation.

series, due to some specific features of the Russian ruble. Taking into account the regime change of the ruble,[3] we decided that a suitable starting point to observe the spillover effect from RTS to the ruble would be January 2008. Also, referring to Charles and Darne (2005 and 2014), who contended that the presence of extreme values (outliers) may have undesirable effects on the GARCH estimates, we decided to exclude observations from the ruble sample in December 2014. In this particular period, extreme depreciation of the ruble occurred due to the Ukrainian crisis and the falling oil prices. Accordingly, the evaluation of the spillover effect from RTS to the ruble was observed in the period from January 2008 to November 2014, and the opposite effect covered the period from January 2002 to November 2014. All nominal exchange rates were observed relative to the euro. Regarding the unavailability of some data because of national holidays and non-working days in asset markets, the daily dates are synchronized between the stock market and the exchange rate market according to existing observations. The concise descriptive statistics account for the first four moments; the Ljung-Box Q-statistics and unit root tests of assets' unconditional distributions are summarized in *Table 1*. All series were collected from Datastream International.

All presented asset return series display abnormal behavior, which is corroborated by the asymmetric features and leptokurtosis. This is verified by low *p*-values of the Jarque-Bera test for all indices and currencies. The LB-Q^2 statistics

[2] Our intention was to observe the period after the completion of the transition process in selected countries. Additionally, in the observed period, the Czech Republic, Hungary and Poland pursued a flexible exchange rate regime.

[3] The Bank of Russia has allowed greater exchange rate flexibility since January 2008.

indicate the presence of time-varying variance in all series, showing clear evidence of an ARCH pattern. The white-noise process was assessed by employing LB(Q) statistics for level and squared returns. According to the estimated values, the LB(Q) test found a serial dependence in all return series. This indicates that GARCH parameterization might be suitable for the conditional variance processes. Due to the presence of autocorrelation and heteroscedacticity, an ARMA process in the mean and the variance equation could successfully capture the dynamics of selected indices. All sample series are subjected to two unit root tests—DF-GLS of Elliot *et al.* (1996) and KPSS of Kwiatkowski *et al.* (1992)—in order to determine whether stationarity holds. The DF-GLS test assesses the hypothesis that the time series contains a unit root and this assumption is accepted unless there is strong evidence against it. On the other hand, the KPSS test examines the null hypothesis of stationarity and it is more suitable in the case of near unit root processes. It can be noted that all DF-GLS tests suggest no unit root in the series, while the KPSS tests indicate that all series are stationary and thus suitable for the further examination.

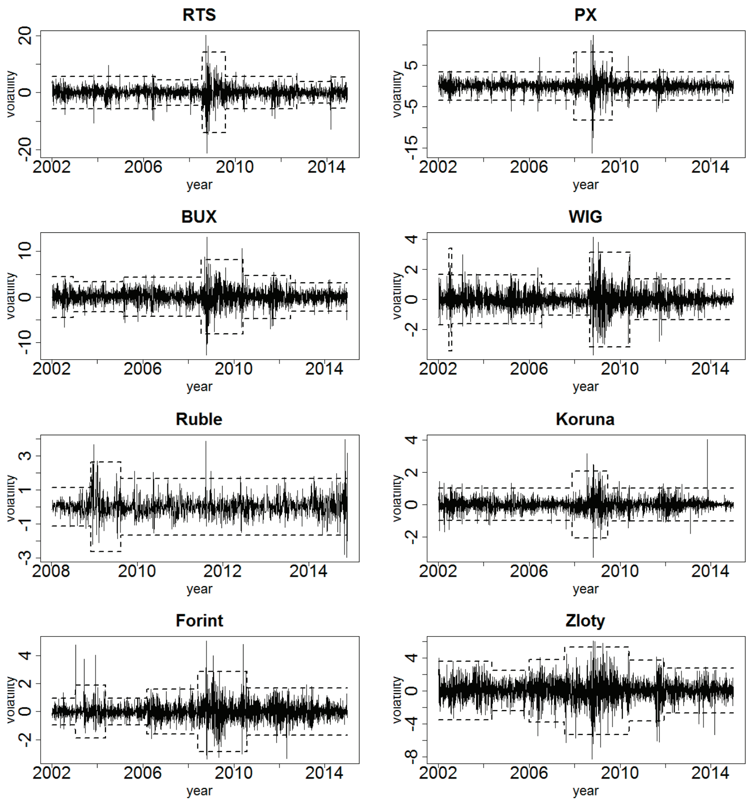
5. Structural Break Detection and Explanation

This section reveals sudden changes in variance applying the modified ICSS algorithm of Sansó *et al.* (2004), which can endogenously identify changes in the variability of observed asset returns. Generally, sudden changes are the result of various domestic and international events, which trigger erratic behavior of various asset returns. As a very suitable tool for detection of sudden changes, the ICSS algorithm has been used extensively by many scholars including Kumar and Maheswaran (2013), Mensi *et al.* (2014) and Kang *et al.* (2011). *Table 2* reports the time periods of sudden changes in volatility, along with standard deviations. *Figure 1* depicts the returns for each index and currency with the multiple points of structural breaks and ±3 standard deviation bands. It can be seen that the number of breaks varies between two and five in all scrutinized asset returns. In the following text, we give a qualitative assessment of possible events that may explain sudden jumps reported by the modified ICSS.

It could be seen that some assets (WIG, BUX and forint) report higher volatility in the period around 2002 and 2003. Increased uncertainty in the asset markets was probably associated with the major global events at that time, which were the terrorist attack on the World Trade Center and the invasions on Afghanistan and Iraq. Thereafter and up to the outbreak of the global financial crisis, almost all Eastern European asset markets enjoyed relatively tranquil periods without breaks, followed by relatively low standard deviations. However, the zloty and forint had several breaking points in the period up to the 2008 crisis. Particularly, these markets had the goal of fulfilling the Maastricht exchange rate stability criterion after entering ERM2. According to Kobor and Szekeli (2004), the changing macroeconomic fundamentals and the unexpected turns of macroeconomic policies as well as the behavior of market participants, i.e. their portfolio-allocation decisions, may be reflected in the amplified volatility of exchange rate market.

The biggest event for all asset markets was the implosion of the sub-prime mortgage bubble in the US and the bankruptcy of several major financial institutions in 2007, which sent shock waves throughout international financial markets. *Table 4*

Figure 1 Daily Returns and Detected Breaks for Selected Indices and Currencies



Note: Dotted lines denote bands of ±3 standard deviations, where change points are estimated using the modified ICSS algorithm.

Source: Authors' calculation.

and *Figure 1* show a steep rise in volatility around that period in all asset markets. Not much later, after stabilization and with tentative signs of recovery, another crisis—the eurozone sovereign debt crisis—struck the EECs. The impact was felt in both stock markets and exchange rate markets, as can be seen in *Figure 1*.

For every structural break detected by the modified ICSS, we create a dummy variable defined as unity from the structural break onwards and zero otherwise. By entering multiple dummy variables in the conditional volatility equation of the particular FIGARCH model, we could test the hypothesis that the presence of structural breaks might cause volatility spillover bias as well as erroneous measures of persistence in the conditional variance and asymmetric effect in GARCH models.

Table 2 Sudden Changes in Unconditional Volatility

Time period	s.d.	Time period	s.d.	Time period	s.d.	Time period	s.d.
WIG		**BUX**		**PX**		**RTS**	
1/3/02–6/21/02	0.559	1/3/02–12/18/02	1.478	1/3/02–12/21/07	1.136	1/3/02–7/13/06	1.873
6/22/02–8/6/02	0.724	12/19/02–2/14/05	1.225	12/22/07–9/2/09	1.636	7/14/06–7/23/08	1.762
8/7/02–7/25/06	0.567	2/15/05–7/29/08	1.335	9/3/09–12/30/14	1.152	7/24/08–8/3/09	2.390
7/26/06–9/4/08	0.507	7/30/08–6/4/10	1.735			8/4/09–12/12/11	2.289
10/4/08–6/7/10	0.659	6/5/10–6/29/12	1.701			12/13/11–3/18/14	2.155
6/8/10–12/30/14	0.449	6/30/12–12/30/14	1.042			3/19/14–11/30/14	1.698
Zloty		**Forint**		**Koruna**		**Ruble**	
1/3/02–5/13/04	1.199	1/3/02–1/16/03	0.316	1/3/02–11/27/07	0.336	1/3/08–12/4/08	0.380
5/14/04–12/30/05	1.057	1/17/03–5/17/04	0.516	11/28/07–6/23/09	0.435	12/5/08–8/18/09	0.647
1/3/06–7/25/07	1.117	5/18/04–3/8/06	0.439	6/24/09–12/3014	0.344	8/19/09–11/30/14	0.558
7/26/07–5/26/10	1.377	3/9/06–6/5/08	0.476				
5/27/10–12/12/11	1.354	6/6/08–8/2/10	0.632				
12/13/11–12/30/14	0.907	8/3/10–12/30/14	0.562				

Notes: The time periods were detected with the modified ICSS algorithm. *s.d.* stands for standard deviation.
Source: Authors' calculation.

Table 3 Volatility Spillover Effect from Foreign exchange Markets toward Stock Markets

	WIG (FIGARCH)[a]		**BUX** (FIAPARCH)[a]		**PX** (FIAPARCH)[a]		**RTS** (FIAPARCH)[a]		**S&P500** (FIEGARCH)[a]
	NB	WB	NB	WB	NB	WB	NB	WB	NB
PANEL A: PARAMETER ESTIMATES									
Mean equation									
C	0.069*	0.070*	0.041***	0.035***	0.057*	0.051*	0.071**	0.065**	-0.003
Ω_1	0.048*	0.045*	0.015	0.013	0.242	0.231	0.075*	0.072*	—
Ω_2	—	—	-0.022	-0.022	-0.096	-0.114	—	—	—
Φ_1	—	—	—	—	-0.205	-0.191	—	—	-0.066*
Φ_2	—	—	—	—	0.054	0.071	—	—	—

	WIG (FIGARCH)		**BUX** (FIAPARCH		**PX** (FIAPARCH)		**RTS** (FIAPARCH		**S&P500** (FIEGARCH
	NB	WB	NB	WB	NB	WB	NB	WB	NB
Variance equation									
ω	-0.025	-0.160**	0.189*	0.557*	0.137*	0.235*	0.092	0.362**	-1.111*
α	0.174*	0.145	-0.017	-0.029	0.124***	0.126***	0.084	0.056	-0.450*
β	0.498*	0.399*	0.157	0.071	0.323*	0.250*	0.307**	0.201	0.854*
μ	—	—	0.272*	0.499*	0.402*	0.609*	0.311*	0.474*	—
δ	—	—	1.656*	1.520*	1.355*	1.265*	1.739*	1.609*	—
γ_1	—	—	—	—	—	—	—	—	-0.224*
γ_2	—	—	—	—	—	—	—	—	0.089*
d	0.342*	0.270*	0.240*	0.157*	0.303*	0.220*	0.285*	0.202*	0.427*
φ	0.368*	0.501*	0.542*	0.514*	0.493*	0.469*	0.717**	0.718**	-0.031
St	7.97*	8.00*	12.54*	12.89*	8.16*	8.70	6.51*	6.85*	8.97*
v	—		—	—	-0.082*	-0.092	-0.093*	-0.095*	-0.151*
PANEL B: STATISTIC TESTS									
LL	-4939.1	-4931.9	-5609.2	-5592.4	-5028.6	-5019.8	-6166.1	-6154.1	-4373.4
AIC	3.0388	3.0374	3.4692	3.4620	3.1003	3.0961	3.9207	3.9162	2.7072
SIC	3.0537	3.0617	3.4899	3.4920	3.1264	3.1260	3.9419	3.9470	2.7278
LB(Q)	19.82	20.17	21.80	20.46	22.81	21.60	12.41	10.81	22.07
LB(Q^2)	27.19	28.22	29.16	29.65	52.46¶	52.87¶	11.42	8.99	28.12
ARCH	1.731	1.799	1.388	1.430	1.694	1.702	0.457	0.321	1.680
P(60)	65.71	79.63	49.11	64.70	63.15	61.12	61.98	71.99	67.22
Skew.	-0.226	-0.206	-0.027	-0.066	-0.298	-0.307	-0.461	-0.496	-0.563
Kurtosis	1.181	1.192	0.647	0.674	1.484	1.397	2.775	3.113	1.538
JB	217.15	216.09	57.00	63.75	346.87	316.09	1123.3	1402.4	491.3

Notes: The WB and NB labels denote models with and without breaks, respectively. *St* stands for the Student tail parameter and *v* is the measure of asymmetry. *LL* stands for the log likelihood information criterion. *AIC* and *SIC* are the Akaike and Schwarz information criteria. *LB(Q)* and *LB(Q^2)* are Ljung-Box Q-statistics for level and squared residuals with 20 degrees of freedom. ARCH denotes the ARCH(LM) heteroscedasticity test with ten lags. *P(60)* is the Pearson's goodness-of-fit statistic for 60 cells. *, **, *** indicate significance at the 1%, 5% and 10% levels, respectively. [a] denotes the LB(Q^2) test for 40 lags.

6. Research Results

6.1 Volatility Spillover from Exchange Rate Markets toward Stock Markets

In order to find the most appropriate ARMA(m,n) model for the mean equation, we estimated several specifications of AR and MA terms up to two lags (m = 0,1,2; n = 0,1,2) for each asset return series. The conventional Schwarz Information Criterion (SIC) was applied to choose the model that best suits the empirical data. Afterwards, we applied an optimal ARMA(m,n) model to four different FIGARCH(1,d,1) specifications with the aim of finding the best fitting one, and decisive criterion was again the SIC.[4] Due to asymmetry and leptokurtosis in the unconditional asset distributions, we considered the standard Student-t and skewed Student-t distributions.

This section presents the results of contemporaneous volatility spillover effects from the exchange rate market toward the corresponding stock market, assuming the best fitting ARMA-FIGARCH process for every stock market. *Table 3* presents the parallel results of the estimated models assessed with and without dummy variables, as well as their diagnostic tests. This comparison is set up in order to test three assertions made by earlier studies, i.e. to see if the presence of structural breaks biases the spillover effect between markets, if the presence of structural breaks increases the long memory in variance, and if it warps the asymmetric effect in the GARCH specifications. Also, for the purpose of comparison, we estimated the impact of the US dollar on the S&P 500 index. All models showed good statistical properties, which are presented by the LB(Q), LB(Q^2) and ARCH tests. None of the models reported obvious problems with serial correlation and heteroskedasticity. Only the LB(Q^2) test for both models of the PX index indicates the presence of time-varying variance at 20 lags, but at a higher lag order it vanishes. Also, the adjusted Pearson's goodness-of-fit test for 60 cells was applied. This test can assess the relevance of various estimated distributions comparing the empirical distribution with the theoretical innovations. The statistical significance of the P-test confirms that the chosen Student-t and skewed Student distributions are relevant for all indices, which is also validated by the significance of the Student tail and asymmetric parameter.

Choosing between model specifications with and without dummy variables, the decision on the optimal model was made based on two information criteria: the maximum log-likelihood (LL) value and AIC. The LL and AIC criteria give an advantage to models with incorporation of structural shifts, thus a viable conclusion is that the models with breaks better explain the empirical series. In most cases, the preferred models, according to the SIC, are the ones without breaks, which is not unusual, as the SIC generally favors more parsimonious models.

The spillover effect is measured by the φ parameter and it is statistically significant in all symmetric and asymmetric FIGARCH models with and without incorporated dummy variables. The results show that this affect is strongest in the Russian stock market. This finding implies that investors in the major Eastern European stock markets are very vigilant and react with the utmost intensity to signs

[4] Tables containing the SIC values of the various ARMA and FIGARCH models can be found in the online *Appendix* (at the web-site of this journal).

of bad news from the exchange rate market. This is an expected characteristic for emerging markets, since gains (losses) in the stock market expressed in a hard currency could be increased (decreased) in the case of appreciation (depreciation) of the domestic currency. Comparing the results of the emerging market stock models to the results of the S&P 500 model, it can be seen that the φ parameter is not statistically significant whatsoever. This is because investors in the US stock market are not so much worried about exchange rate changes, unlike investors in the Eastern European stock markets. In all models, except for the RTS index, the spillover parameter φ is different between two models. This implies that the first hypothesis, which states that the spillover impact could be biased when structural breaks are present, is confirmed.

Secondly, the value of the fractionally differencing d parameter is reduced in every model with included dummy variables, providing evidence of exaggerated volatility persistence, most likely caused by sudden changes in the models without dummies. Thus, the second hypothesis is verified in all examined stock markets. This is also true when we compare our results to the findings of Kasman *et al.* (2009) for Hungary, the Czech Republic and Poland. These authors did not recognize structural breaks in their FIGARCH models, which caused higher volatility persistence in comparison with our results in the aforementioned countries. Since every estimated d parameter has a relatively low value in our models, it means that volatility does not exhibit very persistent behavior, which is closer to the EMH postulates.

Additionally, the parameters μ and δ, which measure volatility asymmetry in the FIAPARCH models of the BUX, RTS and PX indices, are statistically significant and positive, indicating the presence of a leverage effect. The asymmetric reaction of volatility to unexpected news is gauged by the μ parameter, which is positive and significant in all models. In particular, the positive μ term means that conditional volatility is influenced more by negative shocks than positive shocks. Interestingly, all μ parameters in the FIAPARCH models with dummy variables are greater than the same parameters in the models without the employment of structural breaks. This means that structural breaks probably distort asymmetric coefficients in the listed countries, which is confirmation of the third hypothesis.

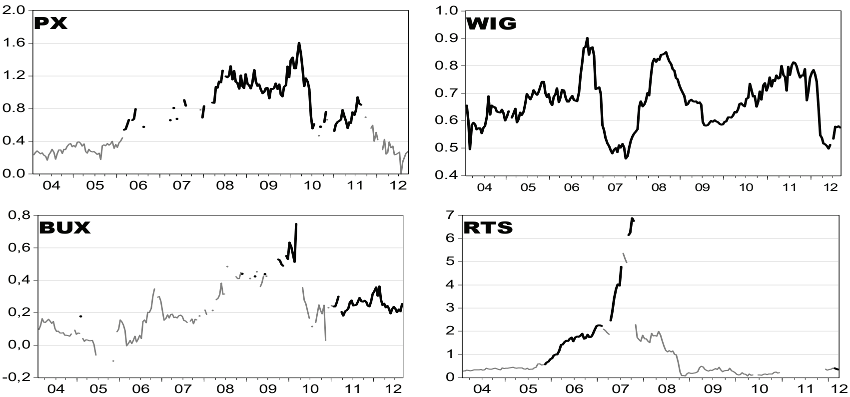
As a robustness check, we performed the same two-step procedure on the weekly returns.[5] These results are in line with the daily data findings in terms of the intensity of spillover between the two markets. Specifically, the spillover effect from the exchange rate market towards the stock market is much higher than in the opposite direction. This was somewhat expected, since we used weekly returns. Also, the fractionally differencing d parameter was reduced in every model after we included dummy variables. Furthermore, volatility asymmetry was not detected in the weekly series.

6.2 Complementary Analysis Using Rolling FIGARCH Methodology

The previous section presented the single point estimates which measure the average effect by observing the whole sample period. However, there are some claims, e.g. by Lin (2012) and Baele and Inghelbrecht (2010), arguing that co-movements between asset markets become stronger during a crisis in comparison to

[5] These results can be found in the online *Appendix*.

Figure 2 Dynamics of Subsequent Rolling Spillover Parameters



Notes: The *X* axis denotes the years and the *Y* axis labels the values of subsequent rolling spillover coefficients. The black line signifies statistically significant φ-parameters at least at the 10% *p*-value and the white line depicts the insignificant φ-parameters. Empty space on the line indicates the absence of spillover parameters resulting from the non-converging models.

Source: Authors' calculation

tranquil periods. In order to test this assertion and see whether the dynamics of the estimated parameters change over time, we utilized a rolling technique that, according to Rapach and Strauss (2008) and Vozlyublennaia (2012), should be used to check whether the results are driven by a particular sample period or not. For this task, we used an optimal FIGARCH model as suggested by *Table 3*. Considering that the observed weeks in average consist of five working days, consecutive subsamples are rolled over in ten-day steps which is approximately two weeks. *Figure 2* presents the results of rolling spillover parameters (φ) with a four-year rolling window.

According to *Figure 2*, it is obvious that the rolling spillover parameters are time-varying and it seems that the spillover effect was stronger during the sub-prime crisis and later sovereign debt crisis in comparison with the periods before or after the crises. This is obvious for the PX and RTS indices, which endured a greater impact from the exchange rate market in the crisis periods. Also, it can be assumed that the presence of both outliers and structural breaks around the period of the global financial crisis caused numerous non-convergences of asymmetric FIGARCH models. This is quite obvious for the BUX, PX and RTS indices. However, we chose to stick to the globally optimal model specifications presented in *Table 3*, even though they may fail to converge in some windows. There are two reasons for this. First, the coefficients are directly comparable. Second, if we choose an entirely different specification for each rolling window in order to avoid non-convergence, we might face an over-fitting problem.

Therefore, *Figure 2* shows that the PX index was subjected to a stronger impact from the FX market during both crises, whereas it seems that the effect was stronger during the sovereign debt crisis. The Russian RTS index suffered a particularly strong spillover impact during the global crisis, while the impact from the exchange rate market faded in the periods before and after the crisis. This finding could explain why the Russian index has the highest spillover parameter in *Table 3*. The rolling results for the BUX index are inconclusive, since the majority of the rolling parameters are not statistically significant. The Polish WIG index suffers the least impact from the exchange rate market, but its φ-parameters are all statistically significant and time-varying during the crisis as well as during tranquil periods.

6.3 Volatility Spillover from Stock Markets toward Exchange Rate Markets

This section analyses the reverse volatility spillover effect, i.e. from the stock market toward the exchange rate market. *Table 4* reveals the results of the optimal asymmetric FIGARCH models, estimated with and without incorporation of structural breaks. All models have very good properties, which is apparent in the absence of serial correlation and time-varying variance. The low values of the LB(Q), LB(Q^2) and ARCH tests are in line with this assertion. Also, the adjusted Pearson's goodness-of-fit tests imply that the chosen Student-t and skewed Student distributions are well suited to the empirical distributions of all the selected currencies. All log likelihood and AIC information criteria give an advantage to models with dummy variables. The SIC criterion prefers a model without breaks and the reason is the same as in the case of the indices.

The reverse volatility spillover effect is measured by the φ parameters, which are all highly statistically significant, except for the ruble model with breaks. In comparison with the results shown in *Table 3*, the contemporaneous volatility spillover effect from the stock market toward the exchange rate market is almost negligible in all exchange rate markets. This outcome could be in line with the expectation, since all the new European Union countries have accepted the obligation of eventual euro adoption, which requires heavy involvement of their central banks in maintaining a stable exchange rate. Furthermore, the central bank of Russia loosened its tight management of the ruble after 2008, though the Bank of Russia continued to carry out large-scale interventions in the domestic foreign exchange market at the same time. These measures were implemented in order to curb erratic capital outflows, slow the ruble's depreciation and prevent instability in the domestic financial markets. This could be the likely reason why shocks from the Russian stock market have the smallest effect on the ruble. Due to these factors, although they are significant, none of the observed exchange rate markets suffers a high magnitude impact from the corresponding stock market, unlike in the opposite case. The American Federal Reserve also intervenes in the USD market, preventing large upswings of the dollar. Therefore, the US exchange rate market, like the EEC exchange rate markets, endures a minor but statistically significant effect from the US stock market, which is in line with previous studies, such as Kanas (2000).

Comparing our results with those of previous studies, our findings are somewhat different from the paper of Fedorova and Saleem (2010), as they reported that only the volatility of the Czech koruna is influenced by the stock market. The probable reason for this is that they observed a different time span and applied weekly returns. No difference in the magnitude of the volatility spillover effect between the models with and without dummy variables can be noticed. Thus, the hypothesis which claims that structural breaks bias the spillover effect cannot be confirmed in the exchange rate markets.

Table 4 Volatility Spillover Effect from the Stock Market toward the Currency Market

	Zloty[a] (FIAPARCH)		Forint[a] (FIAPARCH)		Koruna[a] (FIEGARCH)		Ruble[a] *(FIEGARCH)*		USD[b] *(HYGARCH)*
	NB	WB	NB	WB	NB	WB	NB	WB	NB
PANEL A: PARAMETER ESTIMATES									
Mean equation									
C	-0.009	-0.005	0.005	0.004	-0.003	-0.003	0.003	0.005	0.015
Ω_1	—	—	0.646*	0.635*	-0.201	-0.189	0.120*	0.114*	-0.025
Ω_2	—	—	—	—	0.653*	0.667*	—	—	—
Φ_1	-0.010	-0.014	-0.658*	-0.645*	0.207	0.193	—	—	—
Φ_2	—	—	-0.043**	-0.044*	-0.641*	-0.657*	—	—	—
Variance equation									
ω	-0.009	-0.006	0.010	0.009	-2.216*	-2.226*	-2.082*	-2.379*	0.003
α	-0.059	-0.017	0.181*	0.175*	0.202	0.177	0.829	0.887	0.417*
β	0.101	0.134	0.472*	0.402*	-0.439	-0.433	-0.676	-0.730	0.776*
μ	-0.205*	-0.320*	-0.373*	-0.498*	—	—	—	—	—
δ	1.964*	1.797*	1.390*	1.161*	—	—	—	—	—
γ_1	—	—	—	—	-0.013	-0.011	0.114*	0.106*	—
γ_2	—	—	—	—	0.295*	0.281*	0.287*	0.307*	—
a	—	—	—	—	—	—	—	—	0.003
d	0.248*	0.228*	0.376*	0.311*	0.773*	0.763*	0.676*	0.646*	0.366*
φ	0.022*	0.022*	0.016*	0.015*	0.019*	0.018*	0.007**	-0.024	0.011*
St	10.22*	10.68*	6.32*	6.32*	5.12*	5.22*	6.39*	6.57*	10.09*
v	0.063*	0.076*	0.139*	0.136*	—	—	—	—	—
PANEL B: STATISTIC TESTS									
LL	-2239.0	-2229.5	-2279.1	-2262.7	-892.6	-886.1	-1204.6	-1203.0	-2792.2
AIC	1.3820	1.3793	1.4148	1.4078	0.5567	0.5540	1.4365	1.4363	1.7296
SIC	1.4026	1.4092	1.4393	1.4416	0.5811	0.5821	1.4686	1.4756	1.7465
LB(Q)	14.92	15.43	14.39	15.43	15.16	14.86	21.72	21.07	30.22
LB(Q^2)	25.19	21.91	0.29	0.30	1.89	1.63	11.45	12.04	16.65
ARCH	1.026	0.862	0.016	0.017	0.098	0.091	0.429	0.427	0.158
P(60)	43.04	52.36	63.15	66.00	49.84	48.40	55.03	57.44	69.81
Skew.	0.148	0.174	0.419	0.405	0.315	0.322	0.312	0.226	-0.126
Kurtosis	0.794	0.767	1.053	1.012	1.571	1.553	1.442	1.444	0.792
JB	97.46	96.33	165.08	152.42	390.58	365.12	174.14	161.47	93.42

Notes: See *Table 5*. [a] = the optimal FIGARCH model proposed by the SIC in *Table 3* did not converge, so instead we used the second best model, i.e. FIEGARCH. [b] = we used the HYGARCH model with Student distribution, since it was the first model in a row that could converge.

On the other hand, the fractionally differencing parameter *d* is lower in all models with dummy variables, meaning that the second hypothesis is confirmed. This particularly applies to the Russian ruble and Hungarian forint.

Parameter μ, which measures the asymmetric effect in FIAPARCH, is statistically significant for the zloty and forint. The negative value of this parameter means that currency depreciation increases volatility more than currency appreciation, which is expected. Likewise, the optimal model for the koruna and ruble is FIEGARCH and the γ_2 parameter is statistically significant for both currencies, measuring the magnitude of past errors. Coefficient γ_1 is not statistically significant for the koruna but it is for the ruble. In case of the ruble, it is obvious that a positive shock, i.e. depreciation, causes more volatility, but in the case of the koruna the effect is not clear, since the γ_1 parameter is not statistically significant. It can be seen that all parameters which measure volatility asymmetry in the models are different in the compared models. This might indicate that the presence of structural breaks warps the value of parameters that gauge the asymmetric reaction of volatility to unexpected news.

The subsample parameters of the volatility spillover effect did not demonstrate significant time-varying characteristics, so we neither present nor interpret the rolling FIGARCH results as in Section 6.2.

7. Conclusion

This paper investigates the bidirectional volatility spillover effect between the two most important financial markets in the presence of multiple structural breaks in four selected Eastern European countries. Additionally, we test the hypothesis that structural breaks might cause long-term persistence in variance and distort the asymmetric effect in the GARCH framework. The research was done using the optimal ARFIMA-FIGARCH specifications, and for most asset markets the optimal fractionally integrated GARCH specification includes the asymmetric effect. The modified ICSS algorithm is used to detect multiple structural breaks.

The results indicate that the bidirectional spillover effect exists between the markets, but the impact from the exchange rate market toward the stock market was significantly higher than in the opposite case. The spillover effect was the strongest in the Russian stock market, indicating that investors in that market are the most cautious and react with the most intensity to bad news from the exchange rate market. Complementary rolling FIGARCH analysis also confirmed this assertion, since the influence of the exchange rate market was the highest in the Russian stock market during the period of the global financial crisis in comparison with all other observed countries. Embedding dummy variables into the models according to the modified ICSS findings, we significantly enhanced the performance of our initial models. The findings in all stock markets, except for the RTS index, suggested that the spillover effect is biased when structural breaks are present. Also, this hypothesis could not be confirmed in all exchange rate markets, which is possibly due to the very low spillover effect, due to which there are no major differences between the models with and without dummy variables. The second tested hypothesis was confirmed in all cases, i.e. volatility persistence is exaggerated if sudden changes are not recognized in the models. The last assertion is also confirmed in every asset market, meaning that structural breaks probably distort the asymmetric coefficients in the GARCH models.

We believe that market analysts and fund and portfolio managers could find the results of this study helpful, as they can gain benefits from knowing the magnitude and direction of spillovers between the two markets. Also, investors can improve the risk-adjusted performance of portfolios and thus utilize present inefficiencies in the markets using results obtained by applying long memory models with embedded structural breaks.

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