DYNAMIC NEXUS BETWEEN EXCHANGE RATE AND STOCK PRICES IN THE MAJOR EAST EUROPEAN ECONOMIES

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Abstract

This paper investigates the dynamic conditional correlation (DCC) between stock returns and exchange rate in four East European emerging markets. Due to persistent long memory and the presence of the asymmetric effect in all asset markets we applied DCC-FIAPARCH model. The estimated negative DCC parameters in all scrutinized countries confirmed that portfolio-balanced theory has predominance in the short run in all selected economies. DCC parameters revealed significant time-varying behaviour, especially during the major crisis periods. By embedding dummy variables in the variance equations, we came to the conclusion that global shocks affect the volatility of DCCs. Particularly, it happened during the Global Financial Crisis and European sovereign debt crisis, but the effects were not linearly equal in all countries. Complementary rolling analysis unveils how conditional volatilities of analysed assets influence DCC. The results suggested that exchange rate conditional volatility has higher influence on DCC than stock conditional volatility.

Keywords: exchange rate, stocks, DCC-FIAPARCH, structural breaks, East European countries
JEL Classification: C51, C58, F31, G12

1. Introduction

After the initiation of the transition process, some East European countries decided to switch toward more flexible exchange rate regime as the economic reforms progressed. This applies to relatively large East European economies, such as the Czech Republic, Hungary, Poland and Russia. Due to robust economic growth, gradual disinflation and liberalization of capital account, these countries underwent fairly large capital inflows, as argued by Durčáková (2011). Likewise, financial globalization brought emerging markets under increasing influence of developed markets. In such circumstances, relatively large volumes of capital influx followed by the growing participation of international investors in equity and exchange markets affected demand/supply for domestic stocks and national currency. Eventually, it led to mutual intertwining between equity prices and exchange rate dynamics (Kanas, 2000).

Generally, two theoretical approaches offer an explanation for the interconnection between exchange rate and stocks – the flow oriented model and the portfolio-balance approach. The flow oriented model proposes that appreciation or depreciation of domestic currency decreases or increases the international competitiveness, which eventually affects the balance of trade position as well as firm's cash flow. This tenet focuses on the country's

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current account advocating positive correlation coefficient between the two assets. Some authors, *inter alia*, Matsubayashi (2011), Bartram and Bodnar (2012), Diamandis and Drakos (2011) found the evidence of this relationship. On the contrary, portfolio-balance approach emphasizes capital inflow/outflow which influences demand and supply for the domestic stocks, as well as national currency. This stance proposes that currency depreciation will cause lower demand for domestic stocks and thus lower their value, while currency appreciation will render the opposite effect. According to portfolio-balance hypothesis, negative correlation coefficient describes the connection between these variables. Following studies reported the connection according to portfolio-balance approach: Tsagkanos and Siriopoulos (2013), Boako *et al.* (2015), Lin (2012). The interest of international investor is to be familiar with the relation between these assets, since negative correlation causes the magnification of the gain/losses in the stock market expressed in some solid currency, while positive correlation may offset overall risk.

The aim of this paper is to thoroughly explore the dynamic nexus between exchange rate and stock returns in short run *via* dynamic conditional correlation (DCC), regarding the four major East European countries: the Czech Republic, Hungary, Poland and Russia within a time span of thirteen years. The Czech Republic and Poland have pursued a *de facto* flexible exchange rate during the observed period; Hungary used fixed regime with wide bands, while Russia had applied tight management till 2008 and greater exchange rate flexibility afterwards. Taking into account that various researches, such as Goddard and Onali (2012), Charfeddine and Ajmi (2013), Bentes (2014), reported that long memory persistence in the conditional variance might be intrinsic property of asset series, we empirically relied on the DCC-FIAPARCH model. This particular approach allows measurement of the dynamic interdependence between assets in the short run, assuming fast information flow between two major financial markets. The studies of Moore and Wang (2014) and Caporale *et al*. (2014) also used DCC methodology to investigate the short-run interdependence between stocks and exchange rate. This model also allows measurement of long memory as well as asymmetric effect. Yet, another important issue should be mentioned. It is well known that asset correlations vary over time, *i.e*. market volatility is higher during bearish phases than bullish periods. Numerous authors confirmed this claim; *inter alia*, Syllignakis and Kouretas (2011), Gil-Alana *et al*. (2014). Since our observation span comprises relatively long period, covering two major events – the Global Financial Crisis (GFC)[1] and the European Sovereign Debt Crisis (ESDC)[2], the goal of the study is to perceive how dynamic correlation behave during these phases, *i.e*. whether this connection enhanced and significantly altered during these periods. Since Ulku and Demirci (2012) asserted that there is a lack of research in this area regarding European emerging markets, the contribution of the paper could be referred as two-fold. Firstly, to the best of our knowledge, none of the existing papers gauged dynamic interconnection between these two asset markets *via* DCC-FIAPARCH model in this group of countries. Secondly, the comprehensive analysis of the dynamic correlation was conducted, examining the dependence of the DCC on the assets' conditional variances and the impact of various

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1   According to the Federal Reserve Board of St. Louis (2009), the GFC spans from August 2007– November 2009.

2   According to the European Central Bank source (http://www.ecb.int/ecb/html/crisis.en.html) ESDC lasted from November 2009–April 2010.

shocks on the variance of the Dynamic Conditional Correlation. Our study tries to fill these gaps in the literature.

Besides introduction, the paper is organized as follows. Section 2 presents brief theoretical overview. Section 3 describes methodology and Section 4 considers data employment. Section 5 is reserved for results, *i.e.* DCC estimation and explanation, effects of structural breaks on the DCCs' volatility and the influence of the assets' conditional volatilities on DCC. Section 6 concludes.

2. Brief Theoretical Review

The existence of interrelationship between stocks and exchange rate is well known in the international finance literature. An intense debate on the interaction between these two assets was going over the past 30 years without reaching a consensus. The perplexity is present regarding the particular link between them, as well as the direction and the time span during which it appears. Economic theory distinguishes two main approaches which address this linkage: the traditional or the 'flow oriented' model and the portfolio-balance approach or the 'stock oriented model'. Some empirical evidences support these theoretical stances. For instance, Fang (2002) using daily data for Thailand and the four 'Asian Tigers' disclosed that currency depreciation influences adversely the equity returns and/or increases market volatility over the period of the Asian crisis (1997–1999). Phylaktis and Ravazzolo (2005) analysing a group of Pacific Basin countries over the period 1980–1998 found the evidence which suggests that stock and foreign exchange markets are positively related. Using the dynamic conditional correlation methodology on several developed and emerging Asian markets, the study conducted by Moore and Wang (2014) revealed that in countries with a relatively low degree of capital mobility, economic integration is likely to be the main force of the linkage, supporting the flow oriented model. Otherwise, in countries with high capital mobility, financial integration is the main driving force, supporting the stock oriented model. However, Aloui (2007) asserted that sometimes the precise sign of the correlation between exchange rate changes and equity returns is uncertain because it depends on whether the stock market is dominated by importers or exporters.

The portfolio-balance approach is based on the demand and supply for financial assets. The increased demand for domestic stocks will cause higher needs for domestic currency, which eventually leads to its appreciation. Conversely, if exchange rate appreciates/ depreciates due to some external shocks, it would increase/decrease demand for domestic stocks, which would cause the rise/fall in their value. The portfolio-balance model stands in line with direct relationship between these two variables. Unlike the flow-oriented model, the correlation sign between these two variables should be negative. For example, Liang *et al.* (2013) using the panel Granger causality and panel DOLS methodologies on ASEAN-5 countries found support for the stock-oriented hypothesis. They asserted that exchange rates impact stock prices negatively *via* capital mobility. In another study, Walid *et al.* (2011) utilizing Markov switching EGARCH model and observing four countries (Hong Kong, Singapore, Malaysia and Mexico) found support for portfolio-balance approach since exchange rate has negative sign in the mean equation in all four countries. They concluded that exchange market volatility reduces stock market returns. In Tsai's (2012) paper, six Asian countries were analysed *via* quantile regression approach in order to observe the various relationships between stock and foreign exchange markets. The results indicated a negative relation between stock and foreign exchange markets, but it became

more obvious when exchange rates are extremely high or low. Tai (2007) tested a dynamic integrated international capital asset pricing model, embedding it in an asymmetric multivariate GARCH(1,1)-in-Mean model. This study revealed that a dynamic relationship between stock market and foreign exchange market is consistent with the stock oriented model in six Asian countries. In many research studies which address Asian countries, the portfolio-balance hypothesis was confirmed due to the fact that those countries have become increasingly attractive to foreign capital in recent decades. A similar case could be assumed for emerging East European countries.

3. Methodological Framework

Baillie *et al.* (2007) asserted that common characteristics of daily asset returns is the presence of persistent autocorrelation in their volatility, which opposes to the efficient market hypothesis (EMH) based on martingale. This particular theory contends that knowledge of past events never helps in prediction of the future outcomes. On the other hand, the volatility persistence happens because of the long memory in variance that occurs due to the very slow decay of squared daily autocorrelation coefficients. Methodologies as ordinary GARCH and integrated GARCH are not consistent with long memory problem. Thus, Baillie *et al.* (1996) extended the standard GARCH model with a fractionally integrated process. This approach allows fractional integration $I(d)$ between zero and one, which gives a measure of intermediate process between GARCH and IGARCH. Under the assumption of long memory feature, as well as the other well-known stylized facts of financial time series (volatility clustering, leverage affect, non-normality, *etc.*), we utilize a bivariate dynamic conditional correlation type model for the investigation of dynamic connection between exchange rate and stocks. The conditional variance in the study is modelled by univariate FIAPARCH(1, d, 1) proposed by Tse (1998), because of its capability to capture long memory and asymmetric processes as well. Particularly, the mean and the variance equations have the following form:

$$y_t = C + \Phi y_{t-1} + \varepsilon_t; \qquad \varepsilon_t \sim iid \tag{1}$$

$$\sigma_t^\delta = \omega + \left(1 - (1 - \beta(L))^{-1}\alpha(L)(1 - L)^d\right)\left(|\varepsilon_t| - \mu\varepsilon_t\right)^\delta \tag{2}$$

where $y_t = [y_{1,t}, y_{2,t}]'$ represents 2×1 vector of stock returns and exchange rate changes and $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]'$ is the vector of independently and identically distributed error terms. All series are observed as log returns, *i.e.* $r_{i,t} = 100 \times \log(P_{i,t}/P_{i,t-1})$, where $r_{i,t}$ is the stock market return and $P_{i,t}$ is the stock closing price for some national stock index at time, and $e_{i,t} = 100 \times \log(FX_{i,t}/FX_{i,t-1})$, where $e_{i,t}$ is the exchange rate change and FX is nominal exchange rate of particular currency compared. In order to avoid possible autocorrelation presence, every mean equation contains first lag AR term. The non-normal behaviour of return series is accommodated by the standard Student-t distribution. As for the variance equation, the parameters μ and δ have the following limitations: $-1 < \mu < 1$ and $\delta > 0$. Parameter μ is the leverage coefficient and $\mu > 0$ implies that negative shocks affect volatility more than positive shocks and *vice-versa*. Parameter δ is the power term parameter, and it takes finite positive values. The FIAPARCH (1, d, 1) model allows an intermediate range of persistence, meaning that d parameter lies within $0 < d < 1$. Also, it envelops the other GARCH-type models, meaning that it is equivalent to FIGARCH model when $\delta = 2$ and $\mu = 0$, while it reduces to APARCH model when $d = 0$.

The multivariate DCC model, developed by Engle (2002), comprises two-stage estimation procedure of the conditional covariance matrix H_t. Firstly, for each pair of national stock and exchange rate series a univariate FIAPARCH model is fitted and estimates of $\sqrt{h_{11,t}}$ are acquired. Secondly, asset-return residuals are standardized, *i.e.* $v_{i,t} = \varepsilon_{i,t} / \sqrt{h_{ii,t}}$ wherein the $v_{i,t}$ is then used to estimate the parameters of the conditional correlation. Accordingly, the multivariate conditional variance is specified as: $H_t = D_t C_t D_t$. Where $D_t = diag(\sqrt{h_{11,t}} \dots \sqrt{h_{nn,t}})$ and $h_{ii,t}$ represents the conditional variance, which is obtained from the FIAPARCH model in the first stage. The evolution of correlation in the DCC model is presented as:

$$Q_t = (1 - a - b)\bar{Q} + \alpha v_{t-1} v'_{t-1} + \beta Q_{t-1} \tag{3}$$

where *a* and *b* are nonnegative scalar parameters under condition $a + b < 1$; $Q_t = (q_{ij,t})$ is $n \times n$ time-varying covariance matrix of residuals, while $\bar{Q} = E[v_t v'_t]$ stands for $n \times n$ time-invariant variance matrix of v_t. Since Q_t does not have unit elements on the diagonal, it is scaled to obtain proper correlation matrix (C_t) according to following form:

$$C_t = (diag(Q_t))^{-1/2} Q_t (diag(Q_t))^{-1/2} \tag{4}$$

Accordingly, the element of C_t looks like:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} = \frac{(1 - a - b)\bar{q}_{ij} + a v_{i,t-1} v_{j,t-1} + b q_{ij,t-1}}{\sqrt{\left[(1 - a - b)\bar{q}_{ii} + a v_{i,t-1}^2 + b q_{ii,t-1}\right]} \sqrt{\left[(1 - a - b)\bar{q}_{jj} + a v_{j,t-1}^2 + b q_{jj,t-1}\right]}} \tag{5}$$

where $i \neq j$, and in our bivariate model, *n* is equal to 2. All DCC models were estimated by *quasi* maximum likelihood (QMLE) technique. This procedure allows asymptotically consistent parameter estimates even if the underlying distribution is not normal, as asserted by Bollerslev and Wooldridge (1992).

4. Data Description

Data set used in the paper covers daily observations of four national East European stock indices – WIG (Warsaw Stock Exchange), PX (Prague Stock Exchange), BUX (Budapest Stock Exchange) and RTS (Moscow Stock Exchange) and corresponding currencies – zloty, koruna, forint and ruble. For all assets return series the observed time period ranges from January 2002 to December 2014 and they were collected from Datastream International. The national stock indices were used in local currency terms based on daily closing prices, and the nominal exchange rates were observed relative to the euro. The daily dates were synchronized between two markets according to existing observations, because some data were unavailable due to national holidays and non-working days. Figure 1 displays the daily dynamics of the observed series, which helps in gaining a preliminary insight into the possible short-run relation between these two variables. The presence of direct correlation between the series would point to the flow oriented relationship, while the inverse causality would indicate that the portfolio balance approach is appropriate.

Table 1 displays the descriptive statistics of unconditional distributions of log returns series, *i.e.* first four moments, along with Jarque-Bera test of normality, Ljung-Box Q-statistics tests for level and squared residuals, unit-root tests and the Local Whittle (LW) estimator of Robinson (1995), GSP hereafter. Under the assumption of normality, it is apparent that all series exhibit severe non-normal behaviour with asymmetric distribution and leptokurtosis.

Figure 1 | Plots of Daily Time Series of National Stock Indices and Currencies
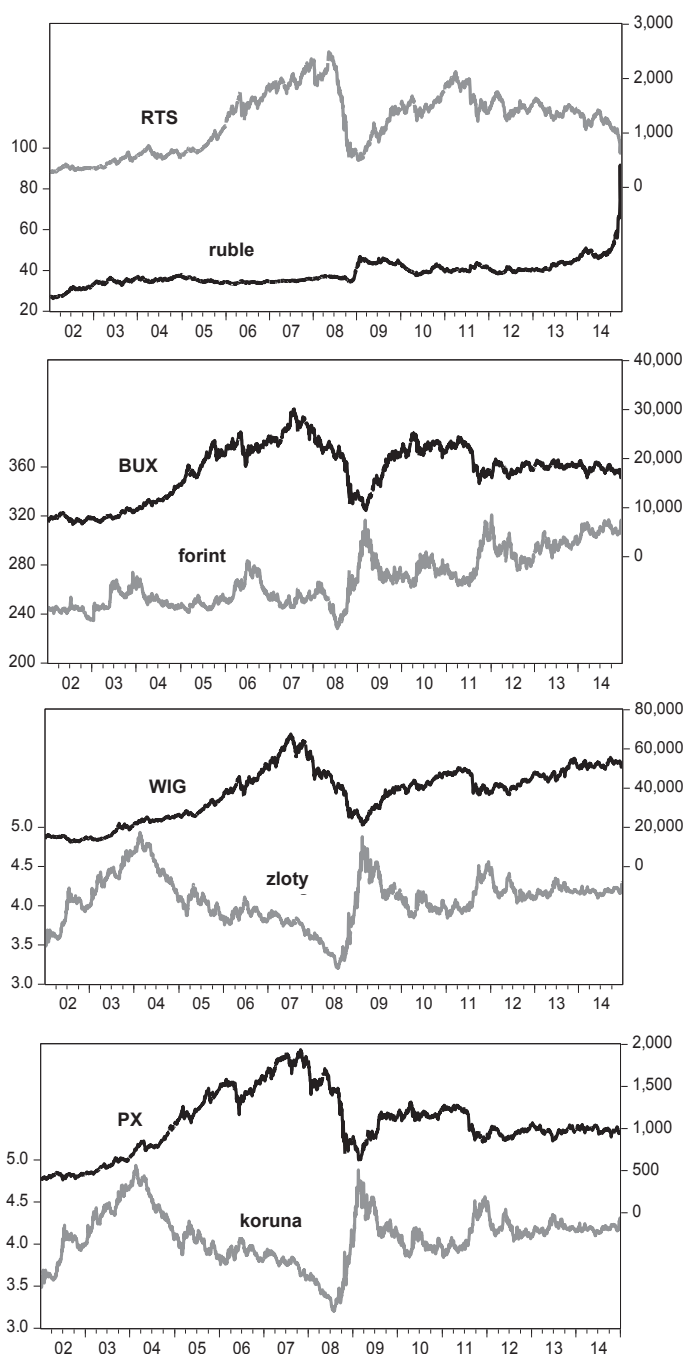
Note: the left y-axis depicts nominal exchange rate values while the right one shows the stock index values.
Source: Authors' calculation

Excess kurtosis with fat tails and a more peaked mean indicates that extreme changes occur more frequently, thus the Jarque-Bera test rejects normality for all series. The common knowledge is that daily frequency financial series are likely to be characterized by leptokurtic distribution, along with heteroscedastic properties. The presence of autocorrelation is confirmed by the LB-Q tests in all the observed series. The LB-Q^2 statistics detect the presence of time varying variance in all series, showing clear evidence of an ARCH pattern, which indicates that GARCH parameterization might be suitable for the conditional variance processes. All the observed series are stationary at very high probability, as suggested by ADF (Augmented Dickey–Fuller) and PP (Phillips-Perron) unit-root test with 20 lags, which dispels any doubts of potentially spurious regression.

Table 1 | Descriptive Statistics, Unit Root and Long Memory Tests

	Indices				Currencies			
	WIG	BUX	PX	RTS	zloty	forint	koruna	ruble
Panel A: Descriptive statistics of the data								
Mean	0.039	0.026	0.027	0.025	0.004	0.007	−0.005	0.040
Std. dev.	1.266	1.596	1.456	2.188	0.594	0.609	0.399	0.894
Skewness	−0.375	−0.102	−0.539	−0.486	0.297	0.671	0.414	5.173
Kurtosis	6.358	9.422	17.098	13.931	8.366	10.791	12.124	178.89
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(Q²)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Panel B: Unit root tests								
ADF(20)	−52.48	−41.41	−41.99	−50.46	−55.46	−42.28	−55.77	−9.63
PP	−52.44	−54.12	−53.49	−50.31	−55.49	−57.01	−55.81	−36.43
Panel C: GSP test – d estimates								
Applied for absolute returns								
m = T/4	0.307***	0.301***	0.345***	0.348***	0.297***	0.305***	0.234***	0.399***
m = T/8	0.418***	0.408***	0.422***	0.430***	0.407***	0.396***	0.376***	0.308***
Applied for squared returns								
m = T/4	0.291***	0.238***	0.331***	0.281***	0.319***	0.222***	0.301***	0.215***
m = T/8	0.398***	0.460***	0.353***	0.324***	0.417***	0.318***	0.294***	0.110***

Notes: JB stands for p-value of Jarque-Bera coefficients of normality, LB(Q) and LB(Q²) test denote p-values of Ljung-Box Q-statistics for level and squared residuals for 20 lags. 1% and 5% critical values of ADF with 20 lags and PP tests assuming only constant are −3.435 and −2.862, respectively. m denotes the bandwidth for rescaled variance test. T is the sample size. *** denotes the statistical significance at the 1% level.
Source: Authors' calculation

Panel C of Table 1 shows preliminary findings of long memory presence in the volatility of stock and exchange rate returns. The analysis was done *via* GSP test conducted on absolute and squared returns, as a proxy of variance. The results suggest that, at very high probability levels, the null hypothesis of no long-range memory should be rejected for all asset series. This is an indication of the persistence of volatility shocks for periods of time longer than the usual exponential decay for which standard GARCH models are appropriate. That suggests that FIAPARCH approach should successfully measure the long memory presence in the DCC of the observed asset series.

5. Research Results

5.1 Dynamic conditional correlation estimation

In this section the dynamic connection between stocks and exchange rate is investigated. Table 2 presents the results of variance equations in four bivariate DCC-FIAPARCH models. The main reason for choosing this model lays in its flexibility to assess the dynamic conditional correlation between two assets, as well as to gauge long memory presence and asymmetric effect.

Regarding the estimated parameters, results show that all asymmetric parameters (μ) are positive and highly statistically significant in all stock markets, meaning that negative shocks cause stronger change in volatility than positive shocks, which is the characteristic appearance on the equity markets. The fractionally differencing parameters (d) lay within range $0 < d < 1$ in all observed stock markets, which indicates that distant volatility realizations are linked in these markets, opposing to EMH stance. The lowest d parameter is noted on RTS index, which could be explained by the fact that Russian stock market, as the largest one, is characterized by the highest level of liquidity and daily volumes of trading. These features allow fast information flowing, which elevates the level of efficiency and reduces the volatility persistence.

As for the currency markets, the negative value of the μ parameter means that a positive shock, *i.e.* currency depreciation increases the volatility more than negative shocks, *i.e.* appreciation, which is expected. This applies to all currency markets except for the Czech. The d parameters are all highly statistically significant in all currency markets, which is, as in the case of stock markets, in line with preliminary findings of GSP test. Russian ruble has the largest long-lasting volatility persistence, and the rationale could lay in the fact that Bank of Russia was conducting predictable tight exchange rate policy until 2008, which contributes to the relatively high d parameter.

For all asset series we performed LB test on level and squared residuals in order to confirm the model adequacy. The obtained results indicate that the hypothesis of no serial correlation and heteroscedasticity should be accepted for all asset return series. Estimates of the multivariate DCC models (a and b) are presented in Panel C and they are statistically significant and nonnegative, satisfying the condition $a + b < 1$. The highly significant t-Student degrees of freedom parameter confirms the adequacy of the chosen distribution. Figure 2 presents DCC plots, which could expose the true short-run connection between these markets, *i.e.* whether they behave in accordance with the flow oriented model or the portfolio-balance approach.
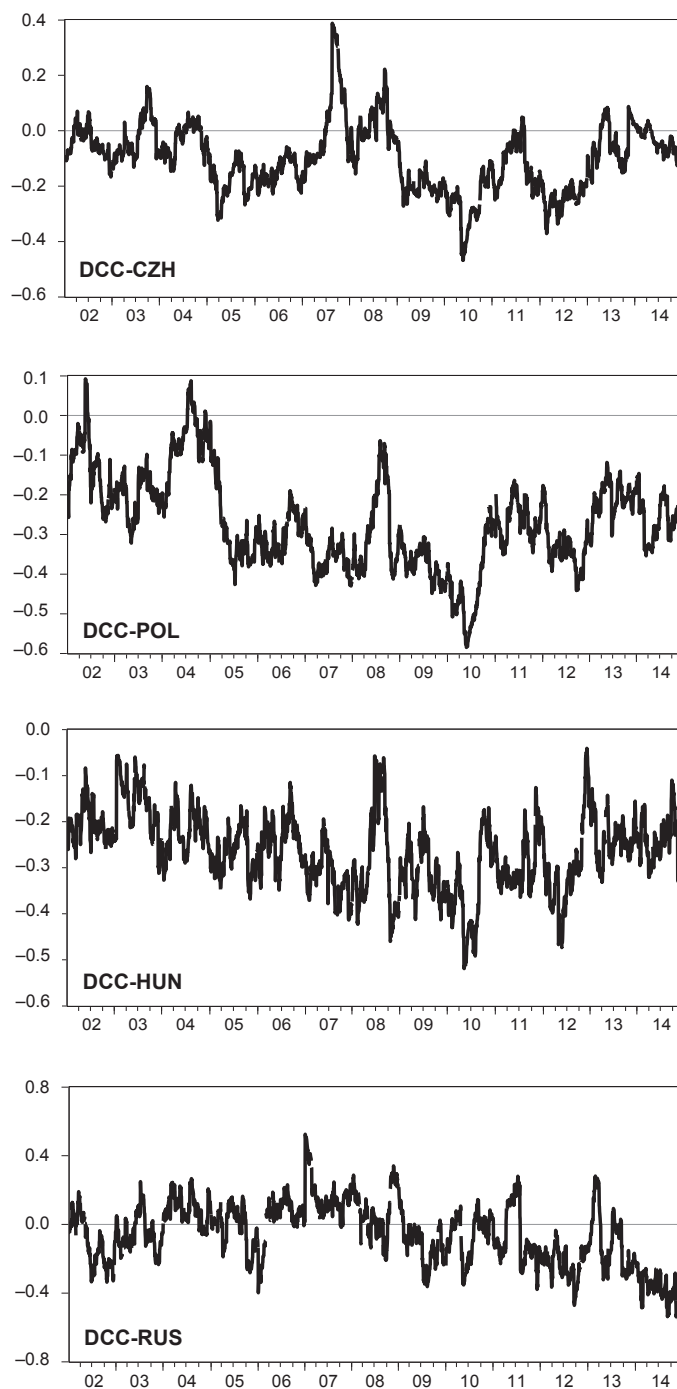
Table 2 | Estimation Results of DCC-FIAPARCH Models

	Hungary	Poland	Czech Republic	Russia
Panel A: Indices				
	BUX	**WIG**	**PX**	**RTS**
ω	2.8376***	2.9624***	2.8036***	3.9712***
α	0.1947**	0.2317***	0.1260*	0.0547
β	0.4761***	0.7011***	0.3910***	0.2837**
μ	0.2680***	0.2084***	0.4215***	0.5253***
δ	0.7379***	1.7665***	1.4496***	1.4389***
d	0.3710***	0.5186***	0.3658***	0.3025***
Diagnostic tests				
LB(Q) 20	21.478	15.785	23.062	11.718
LB(Q^2) 20	9.810	15.854	15.279	22.795
Panel B: Currencies				
	Forint	**Zloty**	**Koruna**	**Ruble**
ω	0.6200*	0.7615***	0.7730***	0.4508**
α	0.1793**	0.2050***	0.3060***	0.4097***
β	0.3729***	0.5665***	0.6310***	0.7595***
μ	−0.6224***	−0.2944***	−0.0200	−0.3192***
δ	1.4805***	1.6382***	1.4614***	1.8335***
d	0.2674***	0.4562***	0.4273***	0.5070***
Diagnostic tests				
LB(Q) 20	22.405	14.991	15.279	22.795
LB(Q^2) 20	1.265	18.202	1.259	22.326
Panel C: DCC parameters				
a	0.019**	0.014***	0.015***	0.031**
b	0.950***	0.981***	0.975***	0.955***
St	7.561***	9.350***	6.730***	7.133***

Notes: LB(Q) and LB(Q^2) test denote p-values of Ljung-Box Q-statistics for level and squared residuals for 20 lags. Parameter S_t denotes the degrees of freedom, measuring the degree of fat-tails of the residuals density. ***, **, * represent statistical significance at the 1%, 5% and 10% level, respectively.

Source: Authors' calculation

Figure 2 | Plots of Dynamic Conditional Correlation

By observing all pair-wise DCC coefficients, it is obvious that predominant inter-dependence between stock and exchange markets is negative in the Czech Republic, Hungary and Poland throughout the whole sample period, and in Russia after 2008, which is in accordance with portfolio-balance theory. It could be seen that DCC increased significantly during 2010 and 2012 in Hungary, Poland and the Czech Republic. This finding is in accordance with claims of some authors, *e.g.* Lin (2012), Baele and Inghelbrecht (2010) and Billio and Caporin (2010) who contended that co-movements between assets markets become stronger after shocks, *i.e.* during the crisis, in comparison to tranquil periods. The first enhancement came after the GFC, which might be explained by increased vigilance of international investors after the major crisis, regarding the fact that negative correlation magnifies the gains/losses in the stock market expressed in some solid world currency. The same assumption could be applied for the second major event – ESDC. Overall findings are in line with the results of Syllignakis and Kouretas (2011) and Moore and Wang (2014).

However, the puzzling appearance is several unexpectedly high positive DCC coefficients, particularly around the periods of GFC and ESDC. These findings are inconsistent with portfolio-balance theory predictions, and the continuous dynamics. The most likely reason could be the presence of the asynchronous shock effects in the corresponding markets. According to the Figure 2, it could be noticed that even before the official bankruptcy of *Lehman Brothers* that took place in September 2008, the foreign investors' sentiment began to deteriorate and EEC stock market started to gain loses, which continued up to the second quarter of 2009. On the other hand, this negative incentive did not transfer to the exchange rate markets immediately. Investors started to abandon national currencies by mid-2008 in case of koruna, zloty and forint, and by the last quarter of 2008 in the case of ruble. Up to that time, the currencies continued to appreciate, particularly koruna, zloty and forint. The pattern of uneven sensibility to external shocks reappeared again, around the period of ESDC. However, the exchange rate markets were first to be affected by this crisis.

In order to gain further insight about the dynamic connection between these markets, in the following sections we tried to identify the factors which had a significant impact on the conditional correlations over the observed period of time.

5.2 The impact of structural breaks on the DCCs

Economic turmoil and financial crisis have significant role in determination of mutual interdependence between stock and exchange rate market. In order to discern the potential influence of major global events on the volatility of DCCs, we employed Bai and Perron (2003) test, which purpose is to detect structural breaks without prior knowledge when those breaks happen. For every break date we created dummy variable, taking unity from the break date onward and zero otherwise. Table 3 discloses several break periods detected by Bai and Perron (2003) test, and Figure 3 depicts actual break points. These breaks may indicate the increased uncertainties in the asset markets. Probably the biggest shock for all asset markets was the collapse of the sub-prime mortgage bubble in the US, which quickly spread throughout international financial markets. Also, the East European markets were greatly affected by the Eurozone sovereign debt crisis. Our findings indicate that these occurrences had a significant impact on the DCCs.

Figure 3 | Detected Multiple Break Points in Dynamic Conditional Correlations
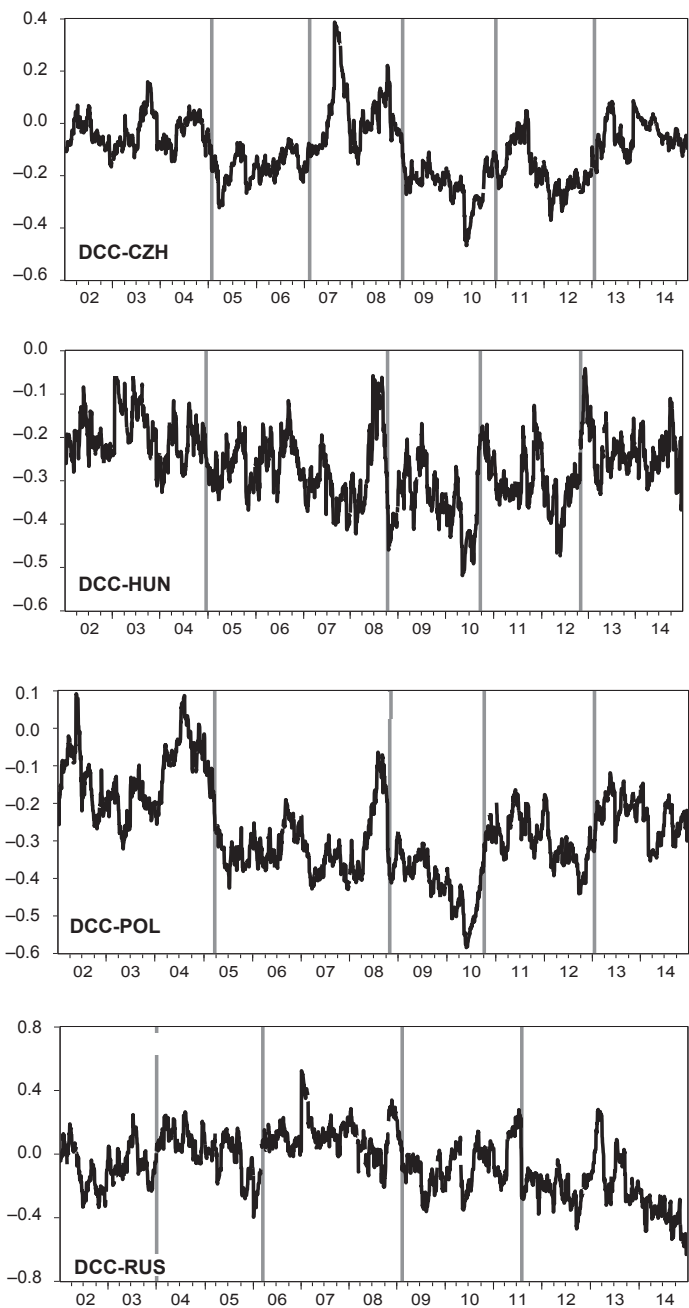
Source: Authors' calculation

Table 3 | Detected Break Periods in Every Dynamic Conditional Correlation

Hungary	Poland	Czech Republic	Russia
1/03/2002 – 12/14/2004	1/03/2002 – 3/16/2005	1/03/2002 – 1/24/2005	1/04/2002 – 1/05/2004
12/15/2004 – 10/06/2008	3/17/2005 – 10/22/2008	1/24/2005 – 2/05/2007	1/06/2004 – 3/17/2006
10/07/2008 – 9/16/2010	10/23/2008 – 10/01/2010	2/06/2007 – 1/19/2009	3/20/2006 – 2/16/2009
9/17/2010 – 10/18/2012	10/04/2010 – 1/11/2013	1/20/2009 – 12/29/2010	2/17/2009 – 8/08/2011
10/19/2012 – 12/30/2014	1/14/2013 – 12/30/2014	12/20/2010 – 1/18/2013	8/09/2011 – 12/30/2014
		1/21/2013 – 12/30/2014	

Source: Authors' calculation

In order to gauge the reaction of the DCCs' volatilities on the crisis events, we followed Dimitriou and Kenourgios (2013) and Chkili *et al.* (2014), and specified four GARCH(1,1) models, inserting the crisis dummy variables in the variance equation. The model looks like:

$$\rho_{ij,t} = C + \Theta \rho_{ij,t-1} + \varsigma_{ij,t} \tag{6}$$

$$\sigma^2_{ij,t} = c + \alpha \varsigma^2_{ij,t-1} + \beta \sigma^2_{ij,t-1} + \sum_{k=1}^{n} \varphi DUM_{k,t} \tag{7}$$

where Θ is autoregressive parameter, α and β measure ARCH and GARCH effect respectively, and ς is white noise error term. Parameter φ stands in front dummy variables.

Table 4 | Estimation of Conditional Variance Parameters

Parameter	Hungary	Poland	Czech Republic	Russia
c	0.0002***	3.31E-05***	3.29E-06	0.0006***
α	0.0213***	−0.0020	−0.0075***	−0.0081
β	−0.0217	0.8575***	0.9935***	0.3836***
φ_1	2.99E-05***	−7.13E-06***	−5.41E-07***	0.0003***
φ_2	1.63E-05**	−1.19E-05***	2.64E-06***	0.0003***
φ_3	−1.27E-05	1.35E-05***	−3.04E-06***	−0.0006***
φ_4	4.00E-05***	5.28E-07	1.14E-06***	0.0002***
φ_5	–	–	1.21E-07	–

Note: ***, ** represent statistical significance at the 1% and 5% level, respectively.
Source: Authors' calculation

Table 4 presents the estimated parameters of conditional variance equations. Disregarding the low values of all structural break parameters, the positive sign before these parameters means that particular break causes higher volatility of the correlation coefficients and *vice-versa*. The estimated coefficients of dummy variables reveal that GFC caused higher volatility of the DCC in Hungary and Russia, while opposite happened in Poland and the Czech Republic. Chkili *et al.* (2014) explained that negative coefficient before dummy variables

could be the result of lower activities in the asset markets. In the cases of Poland and the Czech Republic, ESDC instigate higher volatility of the DCCs, while in Hungary, the dummy 3 parameter is not statistically significant. We did not find the proof of the impact of ESDC on Russian dynamic conditional correlation, since Bai and Perron (2003) test did not recognize the structural shift in the DCC around 2010, when this crisis erupted.

5.3 Dependence of DCCs on the assets conditional correlations

In order to further disclose time-varying interdependence between dynamic conditional correlations and conditional volatilities, we followed Syllignakis and Kouretas (2011) and observed simple linear regression (Equation 8), estimating it with the rolling regression technique. This approach proved to be handy when the intention is to investigate how parameters evolve over time and how they react to the external events. Consecutive subsamples are rolled over by using 252-day rolling window (approximately one year) in ten-day steps, which are two weeks. Table 5 shows ADF test results for dynamic correlations and all values suggest no unit root in the DCC series. Thus, the assumption is that all rolling subsamples are also stationary. Additionally, the possible spurious regression was evaded by using the General Least Squares (GLS) approach, which corrects standard errors for autocorrelation and White method for heteroscedasticity proposed by MacKinnon and White (1985). The linear regression is specified as:

$$\rho_{ij,t} = \Gamma + \Theta_i h_{i,t} + \Omega_j h_{j,t} + e_{ij,t} \tag{8}$$

where ρ_{ij} depicts the estimated pair-wise conditional correlation coefficients between stock returns and exchange rate. Coefficient Γ is constant and Θ and Ω are the rolling parameters, which stand before the conditional volatilities of stock returns (h_i) and exchange rate (h_j), respectively.

The usage of only two regressors in the Equation 8 raises the issue of omitted variables bias, also known as endogenity problem. It is highly likely that other macroeconomic variables such as interest rates, inflation, GDP growth, export *etc*. also affect conditional correlation. However, data series of these macroeconomic variables exist only in lower frequency (monthly and quarterly) and as such, they cannot be included in Equation 8. The alternative is to conduct new research with lower frequency data of exchange rate and stocks, and to combine new DCC series with other macroeconomic variables and see how they influence DCC. This type of research is left to some other studies.

Table 5 | Results of ADF Test for DCC Series

	Hungary	Poland	Czech Republic	Russia
ADF	−5.695	−3.441	−3.689	−4.347

Note: Critical values for ADF test, assuming only constant, are −3.435 and −2.862, for 1% and 5%, respectively.

Source: Authors' calculation

Figure 4 | Rolling Point Estimates of the Conditional Volatilities and FDI Level *per* Years
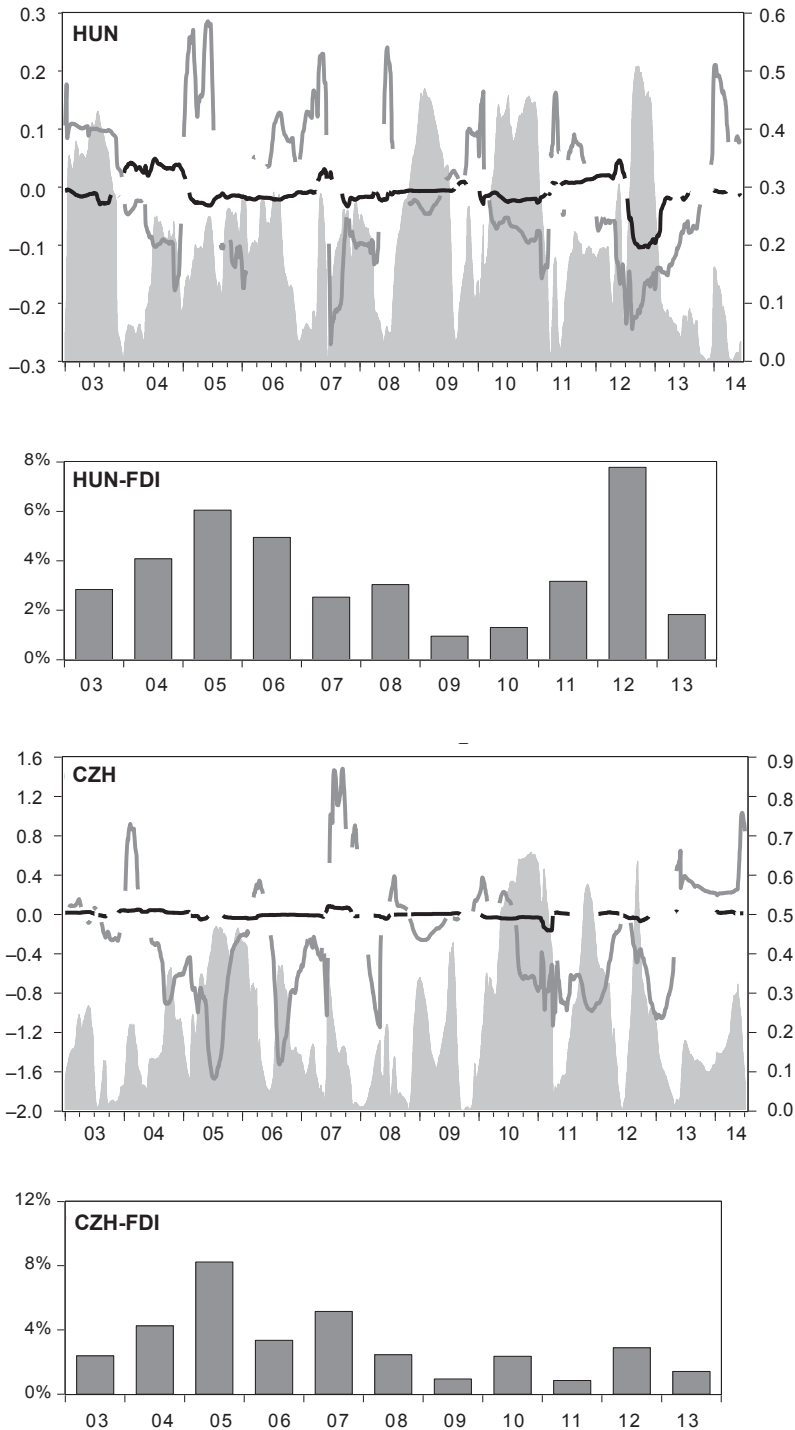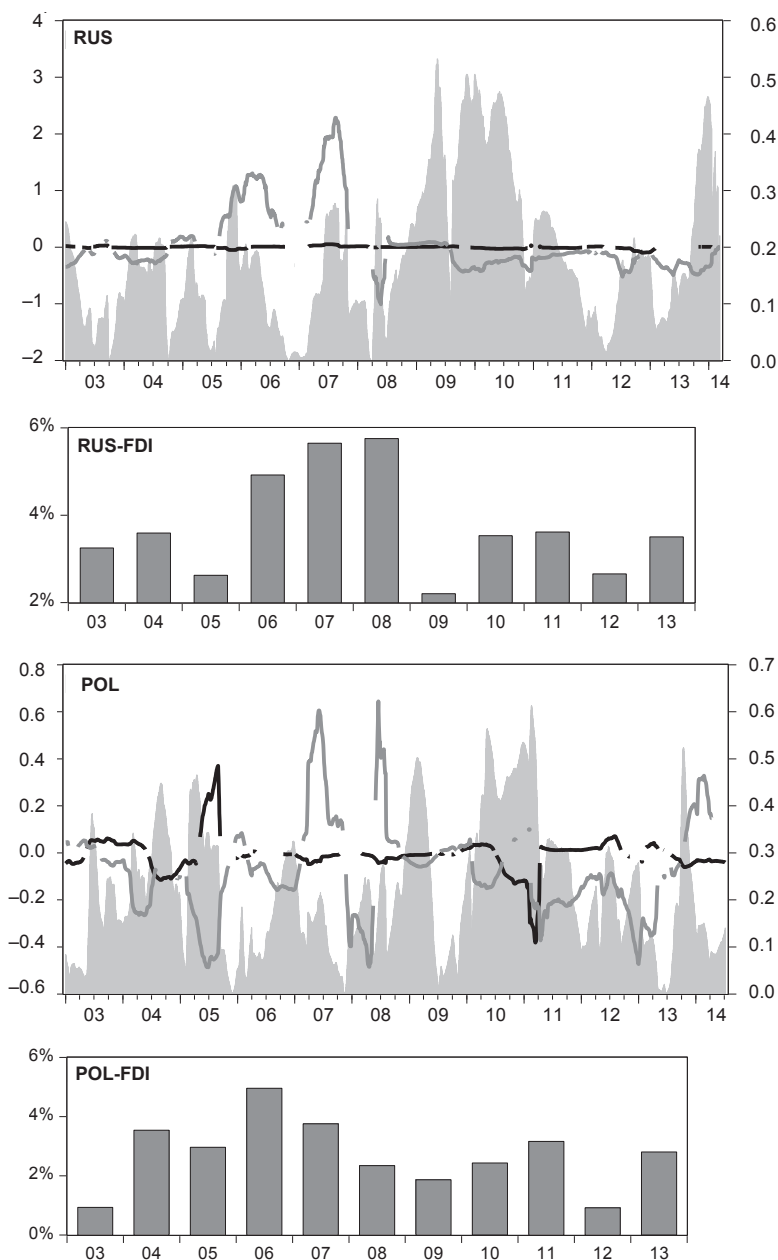
Figure 4 | continuation

Notes: Left Y axis displays the values of conditional volatility parameters and right Y axis the values of determination coefficient (R^2). Black line indicates the statistically significant Θ rolling parameters and grey line presents the statistically significant Ω rolling parameters. The estimated rolling parameters are considered significant only if their p-value is less than 10%. Percentage level of FDIs was calculated by using empirical data of FDI and GDP, collected from http://stats.oecd.org/.

Source: Authors' calculation.

Figure 4 portrays the plotted rolling point estimates of the conditional volatilities, along with rolling R^2 results for each of the four pairs examined. Most of the parameters are statistically significant and time-varying, which is especially true for the parameters of the currencies' conditional volatilities. It implies that exchange rate's conditional volatility has higher influence on DCC than stock's conditional volatility. These findings indicate that international investors are more sensitive to exchange rate oscillations, since currency depreciation offsets gains from the stock market expressed in some solid currency ($, €), while appreciation causes the *vice-versa* effect.

The rolling exchange rate parameters take positive as well as negative values. Positive values indicate that, in the case of negative values of conditional correlations, the rise of conditional volatilities imply negative values of estimated rolling parameters, while positive values of rolling parameters occur when conditional volatilities decrease. Conversely, if the conditional correlations have positive values, the rise of conditional volatilities would yield positive values of estimated rolling parameters, while negative values would occur when conditional volatilities decrease.

Figure 4 shows significantly different values of rolling parameters during different time periods, which is especially true for the exchange rate parameters. Since the volatility is higher in the periods of higher capital flows, it probably implies that exchange rate volatility upswings, depicted in the Figure 4, should be followed by higher capital flows. In that manner, we presented the histogram of foreign direct investment (FDI) share in GDP *per* years, as proxy of capital inflows, below pictures of rolling parameters for every observed country. The comparison of two different pictures leads to conclusion that influence of exchange rate's conditional volatility on DCC is lower during the years of low capital inflow, and *vice-versa*. For instance, the upmost exchange rate volatility in Russia happened in 2006, 2007 and 2008, *i.e.* in the years with the highest FDI inflows. On the other hand, the highest impact of the exchange rate volatility on the DCC in the Czech Republic was in 2005 and in the Hungary in 2012, also in the years with the highest FDIs for those countries. As for Poland, it occurred in 2007, *i.e.* in the year when the FDI level was the second largest.

The explanatory power coefficients (R^2) of the linear model fluctuate considerably across time in all countries. However, taking into account that model (8) considers only two regressors *per* country, determination coefficients are relatively high. It means that conditional volatilities explain DCCs very well, which confirms the legitimacy for the use of rolling regression. Also, it should be noticed that R^2 values were the highest around the year 2010, *i.e.* in the year when ESDC struck and when the currency markets were particularly vulnerable in all selected countries.

6. Summary and Conclusion

The paper explores the dynamic conditional correlation between exchange rate and stocks with an effort to disclose if their short-run relationship is based on the flow oriented model, or on the portfolio-balance approach. Study covers four major East European countries within the time span of thirteen years. Assuming the long memory presence in the variance of asset series and the asymmetric effect, we employed bivariate DCC-FIAPARCH methodology. The estimated DCC parameters indicate that dynamic nexus between these markets is in accordance with portfolio-balance theory in all countries. Our findings suggest that DCC increased significantly during two major events, GFC and ESDC. The probable

reason could be the increased caution of international investors after the major crisis, since negative correlation enhances overall gains/losses, expressed in some solid currency.

Utilizing Bai and Perron (2003) test, we detected several structural breaks in all DCCs. By inserting dummy variables in the variance equations, we tried to determine whether global shocks affected the volatility of DCCs. The estimated coefficients of dummy variables showed clear sign of higher volatility of the DCC during the GFC in Hungary and Russia. On the other hand, conditional volatilities of DCC in Poland and the Czech Republic were more affected by the ESDC.

Additionally, we investigated the influence of conditional volatilities of analysed series on DCC *via* rolling regression. The results suggested the higher influence of exchange rate volatility on DCC. This finding is somewhat expected, since volatile behaviour of national currencies enhances the overall gains/losses, which eventually transfers to the DCC.

We believe that the research could provide beneficial information to portfolio managers and international investors interested in these markets. Better understanding of the dynamic linkage between the markets could help with the decisions related to hedging strategies.

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