3. SUDDEN CHANGES IN VOLATILITY IN CENTRAL AND EASTERN EUROPE FOREIGN EXCHANGE MARKETS

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Abstract

This article investigates sudden changes in volatility of four Central and Eastern European foreign exchange markets using the Iterated Cumulative Sums of Squares (ICSS) algorithm and re-examines the volatility persistence during the period 1999 to 2009. We determined that the identification of sudden changes is associated with local financial, economic and political events, with the exception of the financial crisis as a global factor. The accession to the EU reflects a positive stabilizing effect. Accounting for these sudden shifts in volatility in the GARCH models significantly reduces the persistence of volatility or long memory in the Central and Eastern Europe foreign exchange markets.

Keywords: currency markets, volatility persistence, GARCH models, shifts in volatility, economic and political events

JEL Classification: C12, C58, G15

1. Introduction

In this paper, we examine the sudden changes in volatility in the foreign exchange markets of four new EU members, namely: the Czech Republic, Hungary, Poland and Romania, over the period 1999 to 2009. Moreover, we endeavor to present an overview of major economic, financial and political events of international, regional, or country-specific nature that might have had an impact on the foreign exchange market rates' volatility of the aforementioned countries.

Volatility represents a particular feature of financial series used in investment decisions and, implicitly, in the allocation of resources. Timedependent variations of volatility and, implicitly, of investor-assumed risk have been extensively modeled in

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the 1990s using models of the GARCH family, though this type of modeling has often proved incapable of capturing persistence and sudden breaks in volatility. Volatility persistence manifests itself particularly in daily or intraday return series, through the fact that autocorrelation coefficients in their squared returns often present a slowly diminishing tendency. Following this idea, Baillie *et al*. (1996) and Bollerslev and Mikkelsen (1996) have proposed long memory ARCH models. On the other hand, Lastrapes (1989), Lamoureux and Lastrapes (1990) and, more recently, Granger and Hyung (2004) or Starica and Granger (2005), being skeptical of the properties of the long memory behavior, forward the idea that different structural changes which generate sudden breaks, in some cases, explain the elevated persistence in volatility.

The identification of sudden changes thus becomes quintessential in the construction of new volatility models. The most frequently used method in the literature is the ICSS algorithm proposed by Inclan and Tiao (1994), though studies such as Nguyen (2008) employ the classic CUSUM algorithm. Aggarwal *et al*. (1999) were the first to utilize the ICSS algorithm with the aim of identifying structural breaking points in 10 Asian and Latin American emerging markets. By introducing a dummy variable function in the GARCH model, they have demonstrated that taking into account the structural breaks significantly reduces the volatility persistence.

This conclusion has recently been confirmed by several empirical studies, targeting in particular the capital markets. Hammoudeh and Li (2008) examined sudden changes in volatility for five Gulf area Arab stock markets and found that most of these stock markets were more sensitive to major global events than to local and regional factors. Similar conclusions have been reached by Cheong (2007) regarding the Malaysian stock market, by Kang *et al*. (2009) in the case of the Japanese and Korean stock markets and by Kasman (2009) concerning Brazilian, Russian, Indian and Chinese stock markets. Adversely, Wang and Moore (2009) attributed the sudden changes in volatility of five Central European transitioning markets to more domestic, economic and financial factors rather than to global ones.

Malik (2003) employs the same methodology in the case of foreign exchange markets, through the use of five major nominal exchange rates (against the US dollar). His empirical results indicate that taking into account the breaks brings forth a significant reduction in the volatility persistence and, moreover, that timing of the said breaks corresponds to major political and economic events.

This technique has not been applied to Central and Eastern European foreign exchange markets, considering that there are only a few studies on the subject of volatility regime shifts in these regions. Generally, these studies take interest in a foreign exchange regime's impact on volatility rather than associating its variations to socio-economic and political events. In this line of argument, Kobor and Szekely (2004) use a Markov regime-switching model for four foreign exchange markets in the period 2001 to 2003 whilst identifying two volatility regimes in which the between-market cross-correlations differ significantly. Frömmel (2010) analyzed to what extent the volatility regime modifications of five markets are related to the changes in official exchange rate arrangements. By using the classical GARCH and the Markov switching models, he showed that this relationship is stronger for Hungary and Poland, less so for the Czech Republic, whereas unclear for Romania and Slovakia.

The remaining of the article is organized as follows: Section 2 outlines the methodology; Section 3 describes the data we have used; Section 4 presents the results; Section 5 concludes.

2. Methodology

The goal in the following methodology is to identify first the sudden shifts in volatility of five Central and Eastern European foreign exchange markets with the ICSS algorithm and then to match the time points of variance changes with global, regional or country specific events that occurred across time. Once the breakpoints of variance are detected, two types of GARCH models are estimated: a standard one and one with dummy variables corresponding to the sudden change points as indicated in the ICSS algorithm.

Detecting points of sudden changes in variance – the ICSS algorithm

The ICSS algorithm developed by Inclan and Tiao (1994) is used to detect discrete changes in the variance of exchange rate returns. The algorithm assumes that the series display a stationary variance over an initial time period until a sudden change occurs as a result of a sequence of economic, financial or political events, then the variance reverts to stationary until another market shock occurs. This process is repeated over time, generating a time series of observations with an unknown number of shifts in the variance.

Let $\{\varepsilon_t\}$ be a series of independent observations from a normal distribution with zero mean and unconditional variance σ_t^2. Assume that the variance in each interval is given by σ_j^2, j = 0, 1, ..., N_T, where N_T is the total number of variance changes in T observations and $1 < K_1 < K_2 < \ldots < K_{N_T} < T$ are the set of change points. Then, the variance over N_T intervals is defined as

$$\sigma_t^2 = \begin{cases} \sigma_0^2, & 1 < t < K_1 \\ \sigma_1^2, & K_1 < t < K_2 \\ \vdots & \\ \sigma_{N_T}^2, & K_{N_T} < t < T \end{cases} \tag{1}$$

A cumulative sum of squares is used to estimate the number of variance changes and to detect the point in time of each variance shift. The cumulative sum of the squared observations from the beginning of the series to the *k*th point in time is expressed as

$$C_k = \sum_{t=1}^{k} \varepsilon_t^2 \qquad \text{where: } k = 1, \ldots, T \tag{2}$$

Then, we define the statistics D_k as follows:

$$D_k = \left(\frac{C_k}{C_T}\right) - \frac{k}{T} \quad \text{with } D_0 = D_T = 0 \tag{3}$$

where: C_T is the sum of the squared residuals of the whole sample period.

If the series shows no change in variance over the sample period, then the D_k statistics fluctuates around zero and can be plotted as a horizontal line against *k*. Otherwise, if the series has one or more sudden variance changes, the statistics drifts up or down from zero. In this context, a significant change in variance can be detected based on the critical values corresponding to statistics' distribution under the null hypothesis of stationary variance. The critical values will define the upper and lower limits of the drifts. Thus, if the maximum absolute value of D_k is greater than the critical value, the null hypothesis of no sudden change in variance is rejected. Let *k** define the value of *k* at which $\max_k \left|D_k\right|$ is reached. If $\max_k \sqrt{\frac{T}{2}}\left|D_k\right|$ exceeds the critical value, then *k** is taken as an estimate of the time point at which a sudden variance change occurs. The term $\sqrt{\frac{T}{2}}$ is used to standardize the distribution. The critical value of 1.358 is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{\frac{T}{2}}\left|D_k\right|$. Therefore, a breakpoint in variance will be identified if it exceeds the ±1.358 boundaries in the D_k plot.

However, if the series has multiple change points, the D_k function alone is not powerful enough to identify the breakpoints at different intervals. In order to avoid this deficiency, Inclan and Tiao (1994) developed an algorithm that uses the D_k function to search systematically for change points at different points in the series. The algorithm works by evaluating the D_k function over different time periods, which periods are determined by the breakpoints identified based on the D_k plot. Once the sudden change points are detected using the ICSS algorithm, the regimes of changes in volatility are analyzed with potential factors. The next step consists in estimating the GARCH models without and with changes in variance.

The GARCH model

As mentioned above, once the points of change in variance have been identified, the GARCH model is estimated without and with sudden changes in variance. In the case without sudden changes, the standard GARCH(1,1) model can be specified as

$$Y_t = \mu + e_t \qquad e_t \mid I_{t-1} \sim N(0, h_t)$$

$$h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1} \tag{4}$$

where: $N(\cdot)$ represents the conditional normal density with mean zero and variance h_t and I_{t-1} is the information available up to moment *t*−1. If the autocorrelation function and the *Q*-statistics suggest evidence of significant autocorrelation in the series, then autoregressive terms may be introduced in the main equation.

In order to avoid the deficiency of the standard GARCH model highlighted by Lastrapes (1989) and Lamoureux and Lastrapes (1990), implying that the model overestimates the persistence in volatility when significant sudden changes in variance are ignored, breakpoints should be incorporated into the standard GARCH model as follows:

$$Y_t = \mu + e_t \qquad e_t \mid I_{t-1} \sim N(0, h_t)$$

$$h_t = \omega + d_1 D_1 + \ldots + d_n D_n + \alpha e_{t-1}^2 + \beta h_{t-1} \tag{5}$$

where: $D_1, \ldots, D_n$ are the dummy variables taking the value of 1 for each point of sudden change in variance onwards and 0 for otherwise. Therefore, by incorporating the regime shifts in variance, the persistence of volatility, measured by $\alpha + \beta$, is expected to decrease more significantly than in the case of the standard GARCH model.

3. Data

The dataset consists of the weekly average euro rates against the national currency of four Central European markets, i.e. the Czech koruna, the Hungarian forint, the Polish zloty and the Romanian leu. The study covers the period January 1st, 1999 to December 25th, 2009, yielding 574 observations for each market. Each data series is then converted into weekly logarithmic returns, as follows:

$$R_{t,i} = \ln\left(\frac{C_{t,i}}{C_{t-1,i}}\right) \times 100 \quad \text{for} \quad t = 1, 2, \ldots, T \tag{6}$$

where: $R_{t,i}$ is the return for each foreign exchange rate at time *t* for country *j*, $C_{t,i}$ is the current exchange rate for the European currency against the national currency and $C_{t-1,i}$ is the exchange rate for euro against the national currency, from the previous week.

Table 1 presents the descriptive statistics and the results of the unit root tests for the weekly logarithmic return series of the four markets, for the whole sample period. As shown in Panel A of Table 1, the average returns are positive in all cases with the exception of the Czech Republic, which means that, on average, during the sample period, the euro appreciated against the national currencies. The highest weekly mean return, 0.21%, was reported by Romania, thus indicating, over the whole sampling period, a stronger depreciation of the leu against the euro than the other national currencies. The Czech koruna is the only currency that has shown appreciation against the euro, with an average return of -0.05%. The highest weekly appreciation of the euro against a national currency was registered by Romania, by a maximum value of 8.87%, whereas the most substantial depreciation of the European currency was the one against the Polish zloty, by a minimum of -7.51%.

Table 1

Descriptive statistics and unit root tests

	Czech Republic	Hungary	Poland	Romania
Panel A: Descriptive statistics				
Mean	-0.0492	0.0147	0.00398	0.2061
SD	0.8041	1.0463	1.2352	1.1904
Maximum	3.9745	5.0712	6.4926	8.8722
Minimum	-3.4457	-5.5987	-7.5112	-3.4501
Skewness	0.115	0.497	0.370	1.006
Kurtosis	6.063	7.829	7.909	8.720
Jarque-Bera	225.33*	580.57*	588.44*	878.09*
$Q(16)$	31.75**	22.07	41.74*	44.56*
$Q_s(16)$	180.43*	228.18*	98.26*	96.44*
Panel B: Unit root tests				
ADF	-17.46*	-12.62*	-22.11*	-19.95*
PP	-20.77*	-22.30*	-22.72*	-20.48*
KPSS	0.055	0.036	0.055	0.064

*Notes: The Ljung–Box statistics, $Q(16)$ and $Q_s(16)$, check for serial correlation of returns and squared returns, respectively, up to the 16^{th} order. MacKinnon's 1% critical value is -3.44 for the ADF and PP tests. The critical value for the KPSS test is 0.739 at 1% significance level; * and ** denote significance at 1 and 5% levels, respectively.*

Throughout the whole time period, the volatility, measured through SD, is the highest in the case of Poland, with 1.24%, while the Czech koruna was the most stable currency against the euro, with a SD of 0.8%. Consistent with most of the emerging markets (Aggarwal *et al.*, 1999), all four return distributions are positively skewed and, moreover, the kurtosis indicates fat tails and high peaks corresponding to leptokurtic distributions. Correspondingly, the Jarque–Bera test indicates that the distribution of returns is non-normal. The Ljung–Box *Q*-statistics indicates serial correlation of returns. Therefore, different AR specifications adequate to each return series are required in order to remove serial correlation. AR(2) is used for the mean equation for the Czech Republic, AR(5) is used for Hungary, AR(10) for Poland and AR(9) for Romania. The serial correlation of squared returns suggests the existence of the ARCH effect.

The stationarity hypothesis is verified wibyth three types of unit root tests, namely the Augmented Dickey–Fuller (ADF) test, the Phillips–Perron (PP) test and the Kwiatkowski, Phillips, Schmidt and Shin (KPSS) test. The difference between these tests stands in the null hypothesis, stating the presence of a unit root in the case of the ADF and PP tests and a stationary process in the case of the KPSS test. As shown in Panel B of Table 1, the results of the ADF and PP tests indicate rejection of the null at 1% significance level of a unit root in the weekly logarithmic returns, whereas the KPSS test does not reject the null hypothesis of stationarity at a significance level of 1%.

4. Empirical Results

Sudden changes in variance

The ICSS algorithm calculates the points of sudden change in variance by which different regimes of volatility have been determined throughout the sample period. Figure 1 illustrates the return plots for each series along with the change points and the ± 3 SD during each sub-period of time. Tables 2 and 3 chronologically present the time periods associated with each distinct volatility regime and the corresponding economic, financial and political events, provided by Bekaert and Harvey (2010) and the National Banks official websites.

The Czech Republic. During the whole time period, the Czech foreign exchange market experienced six regime shifts. The first point of change occured in 1999 and may have come as a result of the inflation targeting policies adopted in 1998, aiming at the reduction in the inflation rate from 10.7% in 1998 to 2.1% in 1999. Furthermore, starting in March 2000, the central bank set up measures to ease the appreciation pressure on the national currency and boost economic growth by cutting the interest rates. The beginning of September 2001 marks an increase in the volatility regime, which seems to have been triggered by the intervention of the Czech National Bank against the koruna, after the rise in the currency to a high record against the euro. A significant but short-term jump in volatility during the summer of 2002 seems to be consequential to the worst flooding suffered by Prague and its surroundings in 200 years. The relatively low and stable regime starting in September 2002 corresponds to the economic growth and the financial market reforms taken in order to fulfill the EU accession criteria and enter the EU in 2004. Sincef 2007 the considerably high volatility regime was, more than likely, the effect of the global financial crisis.

Hungary. It displayed four sudden changes in variance, the least in the examined markets. After two short-lived and relatively low regimes mostly associated with political and macroeconomic events, the volatility suffered a sudden increase in May 2000 and kept quite steady for almost 8 years. The main events throughout this period were the adoption of inflation rate reduction policies, the transition to full currency convertibility of the forint, the Hungarian Stock Exchange’s admission as an associate member in the Federation of European Stock Exchanges and the adoption of a set of austerity measures in order to reduce the budget deficit, which alarmingly over-expanded by 2006. The dramatic increase in volatility in 2008 corresponds, yet again, to the impact of the global financial crisis on the national economy. The hit was much harder, as Hungary is highly dependent on foreign capital to finance its economy and has one of the largest public deficits in the EU.

Figure 1

Weekly returns for the four Central and Eastern Europe foreign exchange markets and regime shifts in volatility

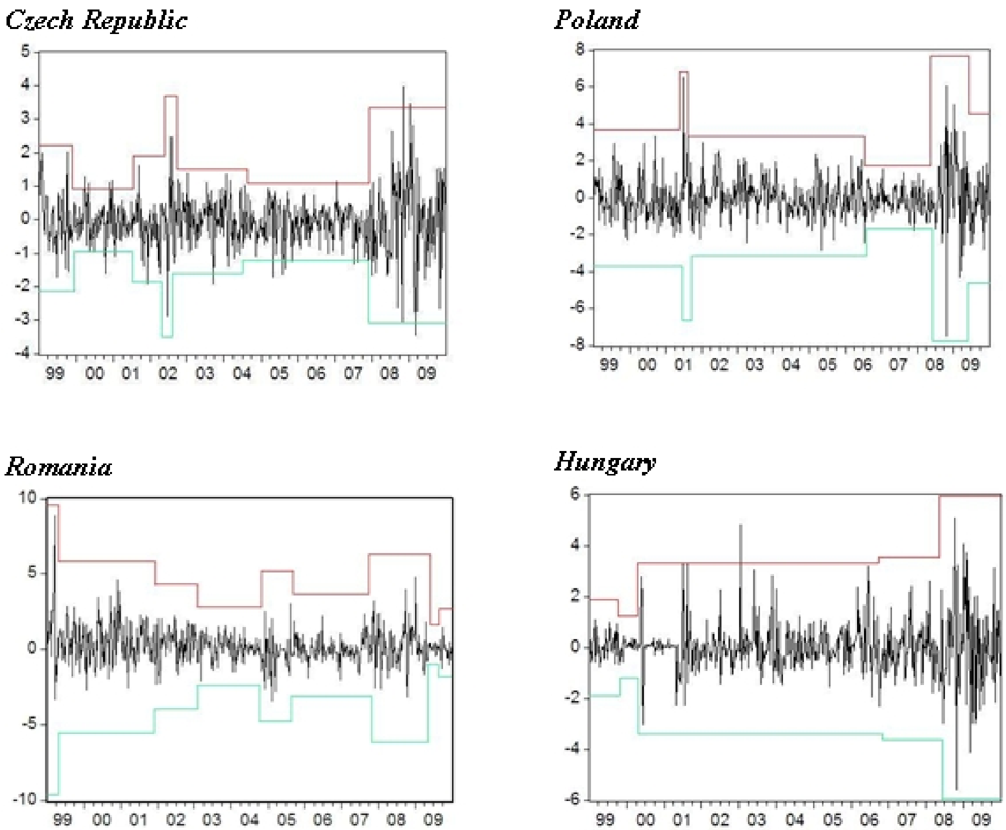

Table 2

Sudden changes in volatility and associated events

The market (no. of change points)	Time period	SD	Events
Czech Republic (6)	8 January 1999 – 15 October 1999	0.88	Elimination of most controls on foreign securities operations. Significant reduction in the inflation rate.
	22 October 1999 – 31 August 2001	0.51	Central bank sets up measures to ease the appreciation pressure on the koruna. Major interest rates cutoffs in order to boost economic growth.
	7 September 2001 – 14 June 2002	0.67	Intervention of the Czech National Bank against the koruna, after the currency rose to a record high against the euro.

The market (no. of change points)	Time period	SD	Events
	21 June 2002 – 30 August 2002	1.57	Prague and its surroundings suffer their worst flooding in 200 years.
	6 September 2002 – 16 July 2004	0.65	Initiation of reforms of the capital market in line with EU directives. Accession to the EU in 2004.
	23 July 2004 – 16 November 2007	0.52	Economic growth
	23 November 2007 – 25 December 2009	1.27	Global financial crisis
Hungary (4)	8 January 1999 – 22 October 1999	0.48	The budget deficit grows by 46% in the first 2 months of 1999, 45% of the overall target for the year.
	29 October 1999 – 12 May 2000	0.22	Strong increase in the real GDP of 6.2% in the first quarter of 2000.
	19 May 2000 – 6 October 2006	0.87	The national currency switches to full convertibility. Admission of the Hungarian Stock Exchange to the Federation of European Stock Exchanges. Accession to the EU in 2004.
	13 October 2006 – 2 May 2008	0.87	Adoption of austerity measures in order to reduce the alarming budget deficit.
	9 May 2008 – 25 December 2009	1.87	Global financial crisis

Notes: The time periods in bold are the volatility regimes for which the corresponding dummy variables were statistically significant in the GARCH(1,1) models, at 5% significance level in the case of Hungary and at 10% significance level in the case of the Czech Republic.

Poland. After a relatively tranquil initial period, a sudden drop by 6% in the zloty, along with the S&P downgrade on Poland's foreign currency debt, translated in a sudden, but short-lasting jump in volatility in the summer of 2001. However, the regime dropped back to initial levels and kept relatively stable for the next 5 years, when the central bank successively cut interest rates against a continuously lowering inflation rate background. At the same time, the zloty steadily appreciated against the euro, following the trend of appreciating currencies across Central European EU applicants to the 2004 accession. Beginning in July 2006, the volatility declined towards the lowest level throughout the sample period, the potential cause being substantial foreign investment inflow. The 2008 sudden increase in volatility can be attributed to the impact of the financial crisis, but the regime decline starting in May 2009 comes as a result of successful anti-crisis measures, Poland being the only EU country to avoid recession and whose economy grew in 2009.

Romania. Out of the markets under discussion, Romania showed the most frequent sudden shifts and the highest initial volatility level, most likely due to a sharp depreciation of the national currency against the USD. The following period was marked by successive falls in the volatility regime, along with the tightening of banking supervision by the National Bank of Romania in May 2000, the intervention of the central bank against a rapid depreciation of the leu in January 2002, the inflation rate's continuous decline and the relatively steady economic growth. Nevertheless, an increase in the volatility regime occurred by the end of 2004, which can be related both to the capital account liberalization in April 2005 and to the national currency denomination by a revaluation of 1:10000 in July 2005. The volatility returned to a lower level starting in August 2005, when direct inflation targeting strategies were implemented by the Romanian government. The regime remained quite stable for about two years, when the national currency became fully convertible in September 2006 and Romania accomplished its access to the EU in 2007. The sudden increase in volatility at the end of 2007 should be largely due to the effect of the global financial crisis and the beginning of the country's economic decline, but the 13 billion euro loan provided by IMF in May 2009 triggered a substantial, but short term fall in the volatility regime.

Therefore, along the sample period, the results showed that the greatest influence on the volatility regime was caused by the 2008/09 global financial crises, causing sudden increases in variance in all cases, though of varying magnitude and time periods, depending on the economic background and the anti-crisis measures adopted by each country. The other common feature was the gradual decline in the volatility regime as the countries approached accession to the EU, followed by a period of calm as the accession was completed.

Table 3

Sudden changes in volatility and associated events

The market (no. of change points)	Time period	SD	Events
Poland (5)	8 January 1999 – 22 June 2001	1.08	Capital in the banking sectors under foreign control reaches 70%. Transition to independent floating exchange rate policy. Launch of the WARSET trading system.
	29 June 2001 – 10 August 2001	2.22	The zloty plunges 6%, the worst drop in 2001. S&P downgrades the outlook on Poland's foreign currency debt from positive to stable.
	17 August 2001 – 14 July 2006	1.01	Successive interest rates cutoffs against a continuously falling inflation rate background. Accession to the EU in 2004.
	21 July 2006 – 25 July 2008	0.72	Massive foreign investment inflow
	1 August 2008 – 24 April 2009	2.62	Global financial crisis
	1 May 2009 - 25 December 2009	1.30	Poland undergoes positive economic growth
Romania (8)	8 January 1999 – 19 March 1999	2.62	Privatization process acceleration. Rapid depreciation of the leu against the dollar.
	26 March 1999 – 1 February 2002	1.36	Tighter banking supervision by the National Bank, as a result of the country's largest fund, FNI, collapse. Intervention of the central bank to stem a rapid depreciation of the leu.

The market (no. of change points)	Time period	SD	Events
	8 February 2002 – 21 March 2003	1.01	Accelerating economic growth and constantly falling inflation rate
	28 March 2003 – 22 October 2004	0.69	Beginning of the restructuring and privatization process of the power sector. Accession to NATO
	29 October 2004 – 5 August 2005	1.18	Capital account liberalization. National currency denomination by a revaluation of 1:10000.
	12 August 2005 – 26 October 2007	0.78	Direct inflation targeting strategies adoption. The national currency switches to full convertibility. Accession to the EU in 2007.
	2 November 2007 – 1 May 2009	1.38	Global financial crisis
	8 May 2009 – 11 September 2009	0.35	IMF provides Romania with a 13 billion euro loan
	18 September 2009 – 25 December 2009	0.66	Plunging into deeper economic recession

Notes: The time periods in bold are the volatility regimes for which the corresponding dummy variables were statistically significant in the GARCH(1,1) models, at a 5% significance level.

GARCH estimation with and without sudden changes in variance

We now investigate the volatility persistence of the four exchange rate return series. The deficiency of the ICSS algorithm lies in the fact that the critical value of 1.358 at a 5% level is inferred under the null hypothesis of independently distributed normal shocks. As argued by Wang and Moore (2009), if the data generating process is a GARCH process, the critical value will be considerably larger due to volatility clustering induced by the GARCH models. Therefore, in order to highlight the presumably false volatility persistence when breakpoints in variance are ignored and to assess the impact of the regime shifts on the volatility persistence once they are taken into consideration, three types of GARCH models are estimated: one that ignores the regime changes, one that incorporates all the breakpoints in variance as determined by the ICSS algorithm and one that includes only significant shift points in variance.

Table 4

GARCH(1,1) parameters with and without dummy variables for sudden change in variance

Country	α	β	$\alpha+\beta$	TR^2	Q(16)	$Q_s(16)$
Panel A: GARCH(1,1) without dummy variables						
Czech Republic	0.0973*	0.8678*	0.9651	0.462	11.13	8.38
Hungary	0.1047*	0.8329*	0.9376	0.102	11.32	4.20
Poland	0.0926*	0.8789*	0.9715	0.308	8.88	5.88
Romania	0.2200*	0.7092*	0.9292	0.589	7.41	20.88
Panel B: GARCH(1,1) with all dummies						

Country	α	β	$\alpha+\beta$	TR^2	Q(16)	$Q_s(16)$
Czech Republic	0.0213	0.5429**	0.5642	0.188	12.28	9.71
Hungary	0.0856*	0.5425*	0.6281	0.011	11.60	9.02
Poland	0.0136	0.7014*	0.7150	1.457	5.37	11.78
Romania	0.1149**	0.3836**	0.4985	0.105	9.19	17.36
Panel C: GARCH(1,1) with significant dummies						
Czech Republic	0.0693*	0.8086*	0.8779	0.895	9.84	16.44
Hungary	0.0848*	0.5459*	0.6307	0.012	11.65	9.04
Poland	0.0403	0.7038*	0.7441	0.963	6.88	9.64
Romania	0.2080*	0.5384*	0.7464	0.509	6.97	18.36

Notes: α is the coefficient for the ARCH term or for the previous shocks. β is the coefficient for the GARCH term or for persistence. (α+ β) is a measure of volatility persistence. TR^2 is an ARCH LM test for autoregressive conditional heteroskedasticity in the estimated variance of residuals. Q(16) is the Ljung–Box Q-Statistics for the 16^{th} lag which tests for serial correlation of residual series. $Q_s(16)$ is the Ljung–Box Q-Statistics for the 16^{th} lag which tests for serial correlation of squared residual series.
** and ** denote significance at 1 and 5% levels, respectively.*

As shown in Panel A of Table 4, when estimating the standard GARCH(1,1) model, which ignores the change points in the volatility regime, the results denote that all estimated parameters are statistically significant at a 1% significance level, in all cases. Consistent with the previous studies conducted on stock markets, the persistence of volatility induced by (α+β) shocks seems to be permanent as the values are close to unit, particularly in the case of Poland. The ARCH LM test and Ljung–Box statistics performed on the residual series indicate acceptance of the null in both cases, i.e. no ARCH effect and no serial correlation of the residuals.

As demonstrated in previous studies, the persistence of shocks to volatility decreases considerably once dummy variables corresponding to the points of sudden change in volatility are incorporated in the GARCH(1,1) model. Panel B of Table 4 shows that the largest drop in the volatility regime is displayed in the case of Romania, by 46.35%, followed by the Czech Republic, by 41.54% decrease. GARCH(1,1) models with significant dummies at 5% significance level have been estimated in the case of Poland, Romania and Hungary and at a 10% significance level in the case of the Czech Republic. According to Tables 2 and 3, the only common major event which significantly affected the volatility of all four return series was the global financial crisis of 2008/09. Re-analyzing the persistence in volatility, as presented in Panel C of Table 4, we find that the results do not show much difference in the case of Poland and Hungary, when comparing GARCH(1,1) models with significant dummies to GARCH models with all dummies. However, the Czech Republic and Romania display an increase in the estimated volatility persistence, from 0.5642 to 0.8779, and from 0.4985 to 0.7464, respectively.

To sum up, the GARCH model, which incorporates significant sudden changes in volatility, confers the highest level of confidence and accuracy of results, since it eliminates both the long memory effect induced by the standard GARCH model and the ICSS algorithm deficiency of overestimating insignificant events.

4. Conclusions

In this paper, we examine the sudden changes in volatility in the foreign exchange markets of four new European Union members using the ICSS algorithm and re-examine the volatility persistence during the period 1999 to 2009.

The sudden changes in volatility have proved to be, for the most part, explained by internal, financial and economic events. Results concur with those of Wang and Moore (2009), showing a significant influence of factors of an internal or regional nature over Central European stock markets. A contrast appears with the works of Hammoudeh and Li (2008) in the case of Arab stock markets of the Gulf region and Kang *et al.* (2009) regarding the Asian stock markets, where events of a global magnitude prevail in significance.

It seems that the accession to the EU reflects a positive stabilizing effect on exchange rates, which persisted until the beginning of the financial crisis. Amongst the analyzed states, Romania represents a distinctive case, due to the presence of the greatest number of sudden changes in the volatility of exchange rates, which could possibly be explained by Romania's high political, economic and financial instability.

As regard the volatility persistence, the highest accuracy results were obtained while incorporating significant sudden volatility changes in the GARCH(1,1) model. Thus, the model's deficiencies related to the false long memory effect of the volatility shocks caused by ignored volatility sudden changes, as well as those caused by overestimated insignificant events when the model incorporates all sudden change points were removed.

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