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Identifying structural changes and associations in exchange rates with Markov switching models. The evidence from Central European currency markets*

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Abstract

Exchange rates can experience structural changes, switching between periods of high and low volatility, which is particularly true with regard to developing countries' currencies. In this paper we model exchange rate daily returns of three Central European currencies against the euro with Hamilton's regime switching model. The goal is to identify periods of high and low volatility, compare the estimates of volatility obtained from the model and the persistence of those volatility regimes between countries and to check whether associations exist between exchange rates with regard to periods of high and low volatility. The results suggest that regime switches in volatility did occur during the 2014–2018 period. The EURCZK exchange rate experienced the lowest volatility, while EURHUF stayed within regimes the longest. The periods of high and low volatility are not independent between countries, with the strongest similarities detected between the EURHUF and EURPLN exchange rates.

Keywords: structural changes, Markov switching model, exchange rate comovement

JEL: C58, G17, F31

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1 Introduction

Identifying structural changes in exchange rate time series with regard to volatility of those rates poses some difficulties. Those difficulties stem from combining two challenges: measuring volatility on the financial markets and analysing the dynamics of financial time series, especially exchange rate returns.

Volatility is an unobservable feature of the financial markets. While it is possible to observe the movement of prices of instruments, it is not possible to observe their volatility. Volatility is therefore approximated with the help of statistical models. Some measures are static (such as the standard deviation and variance) while others are dynamic. The latter is comprised of three groups (Doman, Doman 2009): volatility models such as generalized autoregressive conditional heteroskedasticity and stochastic volatility, implied volatility models that derive volatility measures from market options prices and realized volatility based on high frequency data. While GARCH models specifically were an answer to the problem of volatility clusters evident in financial time series data, they still do not sufficiently deal with structural changes in the data. The dynamics of exchange rates is particularly complex. Many factors influence those rates, some of which (such as market conditions, changes made to the law, political decisions) create a climate for exchange rates and other prices on the financial market to either increase or decrease in volatility. Those periods of high and low volatility are the evidence of structural changes. Structural changes are sometimes mistakenly identified as nonstationary time series or a long memory in the data, which leads to misspecifying the model used to fit the data. Failing to take structural changes into consideration may lead a researcher to false conclusions, especially with regard to data coming from the developing countries.

Identifying periods of high and low volatility (that can be referred to as volatility regimes) on the market is helpful for both the policymakers and financial investors. The former need to be aware of the dynamics of volatility for the purpose of stabilizing currency rates, as may be required by the monetary policy of the country. Financial market participants can also benefit from the knowledge of structural changes in exchange rates. One of the most important characteristics that can influence the strategies implemented by investors is the persistence of those high and low volatility periods measured by the expected number of days spent in each regime before it changes.

Wilfing (2009) concludes that, “volatility regime-switching in exchange-rate data is an empirically significant phenomenon”. From previous research into the topic we learn that changes in regimes of exchange rate volatility for most Central European countries coincide with changes in exchange rate system and monetary policy (Frömmel 2006; Doman, Doman 2007). Furthermore, after the switch to a floating exchange rate system in Poland, some research suggests that exchange rate volatility has remained in a more stable regime, switching into a high volatility regime only for brief periods of time. A gap in research exists with regard to some more recent applications of regime switching models and the identification of volatility regimes in a post crisis reality of exchange rates. Previous studies also established close connections and volatility spillovers between Central European currencies (Kliber 2010; Bubák, Kočenda, Žikeš 2011). The motivation is therefore to revisit the evidence, focusing on a period after the recent global financial crisis.

The aim of the article is to identify periods of high and low volatility on the Central European currency markets using regime switching models to compare the estimates of volatility obtained from the model and the persistence of those volatility regimes between countries, and to check whether associations exist between exchange rates with regard to periods of high and low volatility. The results are based on three exchange rate time series: EURPLN, EURCZK and EURHUF during the period starting in 2014 and ending in 2018. The remainder of the paper is organized as follows. Section 2 discusses the relevant literature. Section 3 introduces the method used in the paper – the Hamilton regime switching model. Section 4 describes the data and section 5 presents the empirical results of the estimation. Section 6 concludes.

2 Literature review

Exchange rate modelling remains at the centre of interest for many researchers. Some of the fields of study include the equilibrium exchange rate or monetary exchange rate models. Examples of those findings were presented by Wdowiński (2010) and Rubaszek and Serwa (2009). Kelm (2013) provides a comprehensive macroeconomic discussion of exchange rate determinants with regard to the EURPLN exchange rate. Bilski, Janicka and Konarski (2013) study the relationships between exchange rate fluctuations of the Central European currencies and the EURUSD exchange rate. Many of the studies mentioned above attempt to shed light on the phenomenon of exchange rate volatility.

In the face of increasing importance of investigating volatility on the financial markets, questions have been raised as to ways of improving the forecasting performance of the traditional GARCH(1,1) model. West and Cho (1995) suggested that models of exchange rate return volatility could be improved by allowing for structural breaks in the unconditional variance of exchange rate returns. Klaassen (2002) suggested improving GARCH volatility forecasts with regime-switching GARCH while Morana and Beltratti (2004) proved that superior long-term forecasts can be achieved by modelling long memory and structural changes in volatility. Evidence in favour of structural changes in the conditional variance has been found by Bollen, Gray and Whaley (2000) as well as Rapach and Strauss (2008). Beine and Laurent (2001) used a Markov-switching FIGARCH model to investigate both long memory and structural changes to find evidence of strong interaction between structural changes and long memory in the field of exchange rate volatility.

Since then, regime switching models have been used to explore structural changes in some exchange rates by Doman and Doman (2007), to model and forecast the volatility of exchange rates (Doman 2005; Frömmel 2004), to provide a framework for the detection of exchange rate regime switching in the run-up to the EMU (Wilfling 2009), or to compare regime switching and policy shifts in CEEC (Frömmel 2006). Very recently a regime switching model has been used to explore the profitability of carry trades by Cho, Han and Lee (2019).

One way of contextualizing the research presented in the article is by indicating its significance to the problem of participation in the Exchange Rate Mechanism II. The Economic and Monetary Union currently consists of 19 EU states, with Poland, Hungary and the Czech Republic obliged to join the eurozone when they are ready, while the convergence criteria are the set of requirements that have to be fulfilled in order for a country to join the EMU. The exchange rate criterion establishes that the achievement of a high degree of sustainable convergence is tested through "the observance of the normal fluctuation margins provided for by the exchange-rate mechanism of the European Monetary System, for at least two years, without devaluing against the euro" (ECB 2012). Biannually, the European Central Bank prepares a Convergence Report to assess the compliance of non-eurozone countries with the convergence criteria. Over the years considerable research has been involved in all matters concerning the fulfilment of the criterion. Bilski, Janicka and Konarski (2013) approached the problem from the direction of currency market convergence, Jurek (2013) proposed a logit analysis to reveal what macroeconomic features favour the stabilization of the Central European currencies' exchange rates while Michalczyk (2014) measured the exchange rate volatility to analyse the stability of exchange rates. This study also delved into this problem by answering a question of how often the Central European currencies' exchange rates switch from a calm to a volatile period. The answer can indicate how difficult it will be for the central banks of those countries to fulfil the convergence criterion.

The research can also be put in the context of volatility spillovers, volatility transmission and contagion. Analysis of those characteristics and their evolution over time is of great importance, influencing the decisions of central bank interventions, international trade, risk management and portfolio diversification (Antonakakis 2012). Contagion can be understood as an increase in relationships between two markets after a moment of turmoil (Forbes, Rigobon 2002). The phenomenon is often studied with the help of static or dynamic correlations (Forbes, Rigobon 2002; Huang, Yang 2003). The research has been greatly improved with the introduction of Engle's dynamic conditional correlation model (Engle 2002). Comovement takes place when markets behave in a similar pattern during a calm period as well as during a crisis (Forbes, Rigobon 2002), while interdependence can be defined as a situation similar to contagion, but in which we cannot distinguish between the infecting market and the infected ones. The method of correlating the instances of high and low volatility on the market presented in the article is intended to revisit the evidence of high interdependencies between the Central European currencies.

Focusing the attention on the Central and Eastern European region, early research has been introduced in works by Fedorova and Saleem (2010). Kliber (2010, p. 281) specifically noticed a strong connection between the volatility of Polish and Hungarian currencies. Bubák, Kočenda and Žikeš (2011) document the existence of volatility spillovers between the Central European exchange rate market, finding that in the pre-2008 period relationships in volatility existed between CZK and PLN exchange rates while EURHUF remained irresponsive and in the post-2008 period volatilities of the currencies reflected mainly their own histories. Hung (2018) focused on the transmission of volatility and volatility spillovers in the Central and Eastern European countries. Comprehensive analysis by Kočenda and Moravcová (2019) focuses on time varying exchange rate comovements and volatility spillovers using DCC models providing proof that during calm periods most of the volatilities on new EU forex markets are independent while during distress periods volatility spillovers increase with HUF assuming the leading role.

3 Modelling regime switches in volatility

Volatility is a measure associated with risk and uncertainty connected with sudden changes in the price of a financial instrument. The simplest way of measuring volatility is to calculate the variance or standard deviation. An example of such an approach can be found in Convergence Reports by the European Central Bank and in an article by Michalczyk (2014), which make use of an indicator called the exchange rate volatility calculated on the basis of the annualized standard deviation of daily percentage changes. Those measures are static, which is their disadvantage. Dynamic measures of volatility overcome that disadvantage and can be grouped into three categories. The advantage of implied volatility models comes from deriving volatility from market option prices. Realized volatility models take advantage of high-frequency data (Będowska-Sójka, Kliber 2010), which in some cases might not be easily available. The last category includes GARCH and stochastic volatility models (Będowska-Sójka, Kliber 2010).

Financial time series (such as price returns) can be characterized by a set of unique statistical properties (Doman, Doman 2009). Some of those stylized facts are: a lack of autocorrelation in returns, leptokurtic distribution with fat tails, asymmetry of positive and negative returns, dynamically changing volatility with high and low volatility clusters, the leverage effect (high negative returns are accompanied by higher volatility than the positive returns of the same magnitude), correlation between volatility and the volume of trade and structural changes evident in the data.

With time a family of ARMA and GARCH models has been developed to fit financial time series with their specific set of characteristics. ARMA-GARCH models allow the exploration of both linear (autocorrelation in returns) and nonlinear (autocorrelation in squared returns) properties found in the data. ARMA is used to model a conditional average in returns. The GARCH model was introduced by Engle (1982) and developed by Bollerslev (1986) and is used to model the conditional variance of the data. The set of equations for $\text{ARMA}(r, s)\text{-GARCH}(p, q)$ are:

$$r_t = \mu_t + y_t$$
$$\mu_t = a_0 + \sum_{i=1}^{r} a_i r_{t-i} - \sum_{j=1}^{s} b_j y_{t-j}$$
$$y_t = \sigma_t \varepsilon_t$$
$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i y_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where $\varepsilon_t \sim \text{iid}(0,1)$, $\omega > 0$, $\alpha_i \geq 0$ and $\beta_j \geq 0$.

In the conditional variance equation alpha parameters account for shocks in squared returns, whereas the beta parameters represent a weighted average of past squared returns. Apart from a Gaussian distribution, ε_t can also be modelled with other distributions: Student's *t*, skewed Student or GED distribution to account for the fat tails of the high-frequency or skewed financial time-series. The GARCH models have been subsequently modified in order to better deal with other issues evident in the data such as long memory or the leverage effect creating a family of GARCH models. They also create the basis for modelling regime switches in volatility.

Modelling regime switches can be done with two types of models (Doman, Doman 2009) depending on whether the regime switches are governed by levels of an observable variable or whether they are governed by a non-observable stochastic process. The first group is comprised of different kinds of threshold autoregressive models (TAR), smooth transition autoregressive models (STAR) or ST-GARCH models. Out of those, only ST-GARCH models are used to switch regimes in the variance equation. The second group of models uses Markov chains to switch between regimes, which means that the probability of being in the current regime is dependent only on the previous regime:

$$P\left(s_t = k_t | s_{t-1} = k_{t-1}, \ldots, s_1 = k_1\right) = P(s_t = k_t \mid s_{t-1} = k_{t-1})$$

Markov chains are used in two types of models: Hamilton's model and MS-AR-GARCH. The latter have been developed in papers by Cai (1994), Hamilton and Susmel (1994) and Gray (1996) and allow for switching regimes in both the conditional mean and conditional variance equation that uses a classic GARCH specification. However this paper focuses on Hamilton's Markov switching model (Hamilton 1989; Hamilton, Susmel 1994). The specification of the model for returns of exchange rates (r_t) is as follows:

$$r_t - m(s_t) = a_1\left(r_{t-1}m(s_{t-1})\right) + \ldots + a_p\left(r_{t-p} - m(s_{t-p})\right) + y_t$$

$$y_t = \sigma_t \varepsilon_t$$

$$\sigma_t^2 = \left(\omega(s_t)\right)\left(1 + \frac{\alpha_1 y_{t-1}^2}{\omega(s_{t-1})} + \ldots + \frac{\alpha_p y_{t-p}^2}{\omega(s_{t-p})}\right)$$

where $\varepsilon_t \sim \text{iid}(0, 1)$ and s_t is the stochastic process governing the regime switching (with two states: 1 and 2); $m(1), m(2), \omega(1), \omega(2)$ are parameters to estimate.

Conditional transition probabilities are also estimated:

$$P(s_t = 1 | s_{t-1} = 1) = p_{11}$$

$$P(s_t = 2 | s_{t-1} = 1) = p_{12}$$

$$P(s_t = 1 | s_{t-1} = 2) = p_{21}$$

$$P(s_t = 2 | s_{t-1} = 2) = p_{22}$$

The p_{ij} probabilities should be non-negative and the following conditions should be observed: $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$. Unconditional probabilities that the switching process will indicate either regime 1 or 2 can be calculated with the following formulas:

$$P(s_t = 1) = \frac{1 - p_{22}}{2 - p_{11} - p_{22}}$$

$$P(s_t = 2) = \frac{1 - p_{11}}{2 - p_{11} - p_{22}}$$

Moreover the average time needed for the s_t process to return to regime i is given by the formula $mtr(i) = \frac{1}{P(s_t = i)}$ while $d(i) = \frac{1}{p_{ij}}$ is the expected duration of stay in regime *i*. This information is of particular interest for a financial investor trying to determine the length of his strategy. The estimation is conducted with the maximum likelihood method. 'Filtered probabilities' and 'smoot hed probabilities' are also a by-product of the estimation. These series should give the best indication of which regime the system is occupying at each date in the sample.

Data description

The raw data set consists of daily EURPLN, EURCZK and EURHUF foreign exchange rates covering the period of 2 January 2014 – 31 December 2018 taken from the stooq.pl database. The amount of observations provides an adequate sample size for the Hamilton model. Since the raw data present a non-stationary process, we use percentage logarithmic returns, calculated with the formula:

$$r_t = 100 * \ln(p_t/p_{t-1})$$

where p_t is a price at time t.

The analysis presented in the article makes use of econometric modelling that was possible with the use of OxMetrics7 software environment, as well as Time Series Modelling 4, which is an extension for OxMetrics used for linear and nonlinear time series modelling, including Markov-switching models. Some of the tests were also conducted with R software environment for statistical computing.

The return series for each exchange rate are depicted in Figures 1–3 in the Appendix. In all three series it is possible to notice periods of higher and lower volatility that can be attributed to structural changes. The descriptive statistics for the time series are presented in Table 1.

Table 1

Descriptive statistics of FX rates' returns (2 January 2014 – 31 December 2018)

	Min	**Mean**	**Max**	**Std. dev.**	**Skewness**	**Excess kurtosis**
EURPLN	-1.7417	0.0023398	2.5064	0.37221	0.35559	3.0897
EURHUF	-1.624	0.0059715	2.118	0.34936	0.11585	2.7670
EURCZK	-1.5959	-0.0051524	0.91821	0.17585	-1.0828	12.082

In all the examined cases the sample mean of the time series is not distinguishably different from zero, given the sample standard deviation and the sample excess kurtosis is highly statistically significant, while sample skewness reveals a different characteristic for each exchange rate. The empirical distribution is skewed to the left for EURCZK returns while EURPLN and EURHUF returns' distributions are skewed to the right. Hence in all cases the returns are not normally distributed, which is confirmed by the Jarque-Bera test. The results of the unit root ADF test confirm that all of the time series are stationary. In addition, with the Box-Pierce statistic we have detected autocorrelation in return series (EURHUF and EURCZK) and squared return series (EURPLN, EURHUF and EURCZK). Moreover ARCH tests reveal that all three of the series are characterized by the ARCH effect.

5 Empirical results

Table 2 presents the estimation results of Hamilton's model applied to each of the exchange rate series. Since the sample mean was close to zero in all time series and estimated m(1) and m(2) parameters were statistically insignificant, a decision was made to re-estimate the models without a constant in the conditional mean equation. A decision was made to use the same model for all three time series with the only difference being a different distribution fitted to EURPLN returns. The decision was made based on information criteria and statistical significance of the parameters of the model.

Table 2

Parameters of the regime switching model for FX rate returns

Variable distribution	(1)		(2)		(3)	
	EURPLN		**EURHUF**		**EURCZK**	
	Student's *t*		**normal**		**normal**	
DF	12.6636 (6.1341)					
a_1	-0.04664 (0.02961)		-0.03403 (0.03096)		-0.18326 (0.03772)	
$\omega(1)$	0.06021 (0.0059)		0.04855 (0.0041)		0.03299 (0.0044)	
$\omega(2)$	0.20353 (0.0239)		0.17954 (0.0179)		0.00077 (0.0001)	
α_1	0.10648 (0.04755)		0.07753 (0.04601)		0.36928 (0.09554)	
Conditional transition probabilities p_{ij}						
Regime No.	1	2	1	2	1	2
1	0.98604	0.019658	0.99464	0.006472	0.98054	0.038584
2	0.013956	0.98034	0.005357	0.99353	0.019459	0.96142

Notes:
Estimated parameters together with standard errors (in parentheses) are reported. Normal distribution or Student's *t* distribution with DF (degrees of freedom) reported.

The EURPLN returns time series can be characterized by two distinct regimes in volatility. Regime one represents a period of lower volatility. The second regime can be described by volatility that is more than three times higher than in regime one. Both regimes are stable, which means that the probabilities of staying in the same regime are high (close to 1), while the probabilities of transitioning to the other regime are low. The estimated number of degrees of freedom in regard to Student's *t* distribution is relatively high, meaning it is more similar to the normal distribution, and therefore contains fewer outliers (the tails are less heavy). The EURHUF returns can also be described by a model with two regimes in volatility. In the second regime the volatility is nearly four times higher in the first regime. The estimated conditional probabilities prove that the regimes are stable. The same can be said about the EURCZK time series, although the regimes are flipped with the volatility in the first regime being over 42 times higher than in the second regime. The differences between regimes are most evident here.

Additional characteristics of the estimated models are presented in Table 3. By comparing the unconditional variances for each regime in each model it is evident that EURCZK is the least volatile exchange rate of the three. The EURPLN and EURHUF exchange rates are on par with each other, although the zloty exchange rate can be characterized with a slightly higher volatility in both regimes. Unconditional variances of the EURPLN exchange rate are much lower than those calculated by

Doman (2005) for the 2000–2004 period, which supports the commonly expressed view of a gradual decrease in EURPLN volatility over the years (Michalczyk 2014).

According to the unconditional probabilities, the EURCZK exchange rate stayed in the lower volatility regime with a higher probability (0.66) than in the higher volatility regime (0.34), which can be interpreted as proof of a much more stable currency. The EURPLN and EURHUF exchange rates behaved in the opposite way. Staying in the higher volatility regime was more likely for both the zloty (0.58) and forint (0.55) exchange rates against the euro.

Table 3

Additional characteristics of the estimated models (expected duration of stay, average time needed to return, unconditional regime probabilities and unconditional variances of each regime)

Variable	**EURPLN**	**EURHUF**	**EURCZK**
	(1)	**(2)**	**(3)**
d(1)	50.87	154.51	25.92
d(2)	71.65	186.69	51.39
mtr(1)	2.41	2.21	2.98
mtr(2)	1.71	1.83	1.50
$P(s_t = 1)$	0.42	0.45	0.34
$P(s_t = 2)$	0.58	0.55	0.66
$\sigma^2(1)$	0.067385	0.05263	0.052305
$\sigma^2(2)$	0.213691	0.19463	0.001221

Finally, by looking at the expected duration of stay in each regime it is possible to ascertain how often the currency switches form periods of high volatility to low volatility and answer how long an investor can expect those conditions to last. The structural changes are rarest in the EURHUF exchange rate. The periods of high volatility are expected to last approx. 187 days, while the periods of low volatility last approx. 155 days. The regime stays are much shorter in the case of EURPLN exchange rate. The periods of high volatility are expected to last approx. 72 days, while periods of lower volatility last approx. 51 days. The Czech koruna exchange rate changes regimes most often. The periods of high volatility are expected to last approx. 26 days, while the periods of low volatility are longer, lasting approx. 51 days. A previous study by Doman (2005) suggested that the EURPLN exchange rate experiences only very brief (approx. 1 day) increases in volatility, while the calm periods last approx. 140 days. The research was based upon the data ranging from 2000 to 2004, and since then Polish financial markets have become much more globalized with a significant increase in short-term foreign capital. The influence of global sentiments can be responsible for that change.

The models also allowed the estimation of smoothed conditional probabilities, which give the best indication of which regime the system is occupying at each date in the sample. If the smoothed probability at a given day is higher than 0.5, one can reasonably assume that the day's exchange rate return is generated by the first regime's model, while probability lower than 0.5 signifies the second regime as the governing process. With that approximation it is possible to divide the research period into subperiods of higher and lower volatility. Figures 4 to 6 in the Appendix present those subperiods as a background with conditional variances estimated by the model and squared returns as an approximation of realized volatility. By comparing squared returns with the estimated variance and the highlighted periods it is evident that the model correctly identified periods of higher and lower volatility and therefore can indeed be used to adequately estimate volatility on the Central European currency markets.

Table A.1, which divides the period of analysis in this paper into subperiods of high and low volatility for each exchange rate based on the previous calculations, is available in the Appendix, as well as Table A.2, which represents the percentage of days with high volatility in each quarter for each exchange rate.

Previous research suggested that exchange rate system and monetary policy changes are indeed reflected by changes in volatility regimes as modelled by Markov switching models. Doman and Doman (2007) attributed the structural changes in the EURPLN exchange rate to changes in the exchange rate regime. Frömmel (2006) noted that the results are most pronounced for Hungary and Poland as well as that an increase in the flexibility of the exchange rate regime leads to an increase in exchange rate volatility. Even though such drastic changes have not been common during the period covered in this study, an important decision was announced in April 2017 by the Czech National Bank. It finished its 3.5-year commitment to intervene on the foreign exchange market and maintain the exchange rate close to CZK 27 to the euro. This coincides with a change from a calm to a high volatility period as can be seen on Figure 6. The structural break in EURCZK exchange rate can therefore be explained by the change in the monetary policy environment and is entirely in line with previous research. However, it is important to note that structural breaks can also be detected in exchange rates that have not been subject to exchange rate system changes – EURPLN and EURHUF. Floating exchange rate regimes expose those currencies to a variety of short-term factors influencing volatility: changing risk premiums, short-term capital flows and the effects of news announcements, to name a few.

The next step is to check for any associations, dependencies or relationships between the currencies in regard to their periods of high and low volatility. Three time series were constructed consisting of only binary data, with "1" meaning that on that day the currency was in a period of low volatility and "0" meaning that the currency on that day was governed by the high volatility regime. This allowed for three 2×2 contingency tables to be constructed that became a basis for employing a Chi-squared test of independence for two discrete binary variables. The Pearson's Chi-squared test can answer whether the distribution of high and low volatility for one currency is independent of the distribution of periods of high and low volatility for the second currency.

Table 4
Pearson's Chi-squared test with Yates' continuity correction results for each pair of variables

	EURPLN	**EURHUF**	**EURCZK**
EURPLN			
EURHUF	96.974 (p < 2.2e-16)		
EURCZK	10.569 (p = 0.00115)	12.98 (p = 0.0003149)	

Note: Chi-squared statistic reported along with p-values in brackets.

The results of Pearson's Chi-squared test with Yates' continuity correction are reported in Table 4. The null hypothesis of independence is rejected in favour of the alternative in all three cases. Therefore a conclusion can be reached that relationships in fact exist between all three pairs of exchange rates with regard to the periods of high and low volatility. To confirm these findings, Fisher's exact test was also conducted. Fisher's exact test also uses independence as the null hypothesis but makes use of odds ratios as the basis of the test. The results of this test confirm the previous findings. There is enough evidence to reject the null hypothesis that periods of high and low volatility in each pair of exchange rates are independent of one another.

Table 5
Fisher's exact test results for each pair of variables

	EURPLN	**EURHUF**	**EURCZK**
EURPLN			
EURHUF	3.151431 (p < 2.2e-16)		
EURCZK	0.6759588 (p = 0.001055)	0.6759588 (p = 0.001055)	

Note: Odds ratios reported along with p-values in brackets.

Determining the exact nature of the relationship requires evaluating the similarity between binary variables. A widely used measure of association for two binary variables is the phi coefficient introduced by Karl Pearson, which is similar to the Pearson correlation coefficient in its interpretation. The phi coefficient varies from -1 to 1 with -1 and 1 indicating perfect associations. The results of the calculation of the phi coefficient for each pair of variables are reported in Table 6. Two other measures of similarity in binary data were calculated to confirm the findings: Yule's binary similarity coefficient (which also ranges from -1 to 1) and Jaccard's binary similarity coefficient (which ranges from 0 to 1). The results for each pair of variables are reported in Tables 7 and 8.

Table 6
Phi coefficient for each pair of variables

	EURPLN	EURHUF	EURCZK
EURPLN	1		
EURHUF	0.2758554	1	
EURCZK	-0.0922075	0.1019855	1

Table 7
Yule's binary similarity coefficient for each pair of variables

	EURPLN	EURHUF	EURCZK
EURPLN	1		
EURHUF	0.5185821	1	
EURCZK	-0.1935092	0.2132381	1

Table 8
Jaccard's binary similarity coefficient for each pair of variables

	EURPLN	EURHUF	EURCZK
EURPLN	1		
EURHUF	0.4973147	1	
EURCZK	0.2351097	0.3014354	1

All three coefficients support the same general conclusions. The phi coefficient informs us that the similarity between the binary variables representing periods of high and low volatility is strongest (however still weak) between the EURPLN and EURHUF exchange rates and weakest between the EURPLN and EURCZK exchange rates. In the case of EURPLN and EURCZK, the variables seem to be negatively associated, meaning periods of high volatility for one exchange rate coincide with periods of calmness for the other. However, it is important to note that the strength of this relationship is very weak. The Yule's coefficient makes all of the similarities appear stronger than measured with Pearson's phi, but the results support the same conclusions. Jaccard's coefficient also suggests that the similarity between periods of high and low volatility is most pronounced when comparing EURPLN and EURHUF exchange rates with nearly half of the distance between the binary variables covered. The similarity is less pronounced between EURHUF and EURCZK or EURPLN and EURCZK.

The results can be interpreted as evidence of volatility spillover between the Polish and Hungarian currencies that does not constitute contagion but rather comovement or interdependence, since the significant level of market correlation suggests strong linkages between the two economies that exist in all states of the world – both calm and volatile (Forbes, Rigobon 2002). Unidirectional volatility spillover between these currencies has also been found by Kliber (2010, p. 295), Fedorova and Saleem (2010) and Bubák, Kočenda and Žikeš (2011), while a bidirectional volatility spillover as well as high correlation of exchange rates, both pre and post 2008 global crisis, has been documented by Hung (2018). However Fedorova and Saleem (2010) have also found other evidence of integration of Central European markets within the region, such as volatility spillovers between the Czech and Hungarian or Polish and Czech currencies. While the results of independence tests offer some limited support to the idea of close integration of these three currency markets, further measures of association between calm and volatile periods (with the exception of Poland and Hungary) do not seem to agree. Some understanding can be gained by further results given by Bubák, Kočenda and Žikeš (2011) and Hung (2018). Both studies agree that foreign exchange markets in Central European countries became more independent during and after the global financial crisis, with exchange rate volatilities mostly reflecting their own history and correlations between them decreasing in comparison to the pre-crisis period. Kočenda and Moravcová (2019) also note that during calm periods most of the volatilities of Central European currencies are due to each currency's own history, which would explain the lack of significant correlations (with one exception) with regard to high and low volatility regimes. However, they also find that during distress periods volatility spillovers among currencies increase substantially and HUF assumes a leading role. In that regard, the results by Kočenda and Moravcová (2019) differ from Bubák, Kočenda and Žikeš (2011).

6 Conclusions

The aim of the article was to identify periods of high and low volatility on the Central European currency markets using regime switching models, to compare the estimates of volatility obtained from the model and the persistence of those volatility regimes between countries and to check whether associations exist between exchange rates with regard to periods of high and low volatility.

We estimated Hamilton's regime switching model for three exchange rates of Central European currencies vis-à-vis the euro and note that their dynamics are well suited to this kind of model. The EURPLN exchange rate experienced periods of high volatility mostly in 2015 and 2016, for EURHUF the volatile period stretched between the beginning of 2014 till March 2016 and the EURCZK exchange rate was relatively volatile throughout 2014 and 2015 but also 2017 and 2018. However, by comparing the unconditional variances for each regime in each model it becomes evident that EURCZK is the least volatile exchange rate of the three and also more likely to stay in the lower volatility regime than in the higher volatility regime. On the whole it can be noted that the period from the beginning of 2014 until July 2016 was more volatile for all three currencies, while the period of mid 2016 till the end of 2018 was relatively calm (with the exception of the middle of 2018).

The persistence of higher and lower volatility periods differs between exchange rates as well. The most persistent exchange rate is the EURHUF, with expected time of staying within a regime estimated as 5–6 months. The EURPLN and EURCZK exchange rates enjoy the same regime for approx. 1–2 months. This kind of regime switch can have extreme repercussions for a central bank expected to stabilize an exchange rate. It is also important to note that similarities between the periods of high and low volatility between the countries do exist up to a certain degree. The currencies' volatility regimes are not independent of each other, which suggests a common component driving and influencing the volatility of Central European currencies. EURPLN and EURHUF appear to have at least a moderate degree of similarity with regard to the volatility regime, while EURCZK behaves more independently of EURPLN and EURHUF.

Policymakers need to be aware of the possibility of structural breaks happening in the exchange rate in reaction to monetary policy shifts, as evidenced by the volatility regime switch following Czech National Bank's decision in April of 2017. Regime switches are, however, not only characteristic of events such as exchange rate system changes, but can also be a useful tool for analysing the patterns evident in recent exchange rate behaviour. The higher frequency of volatility switches in EURPLN and EURCZK exposes the vulnerabilities of those currencies to market "mood swings". That will make it more challenging to stabilize those exchange rates in the ERM II. The vulnerability of EURPLN can also be attributed to an increased association between periods of high and low volatility found in the data. While the results of independence tests confirm a certain degree of integration or convergence happening between Central European currencies, it can be seen as a risk factor when it is reflected in contagion between the markets. The findings support the idea of comovement or interdependence between Polish and Hungarian exchange rates vis-à-vis the euro, but otherwise periods of calmness and high volatility on the currency markets seem to be rather independent in recent years. While it should make the process of stabilizing the EURCZK exchange rate easier than EURHUF and EURPLN, it does not preclude an increase in volatility spillovers during a crisis, as suggested by Kočenda and Moravcová (2019). The paper does not include sensitivity tests as well as a comparison of findings over a longer time horizon. This remains, however, a future research topic.[1]

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[1] I thank an anonymous reviewer for pointing this out.

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Appendix

Figure 1
Daily EURPLN returns

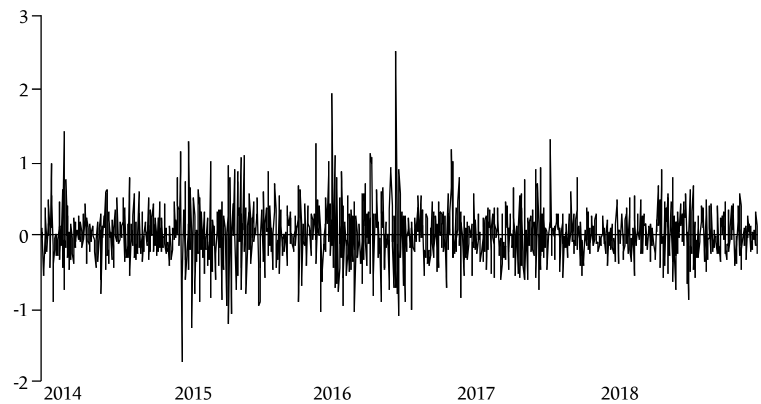

Figure 2
Daily EURHUF returns

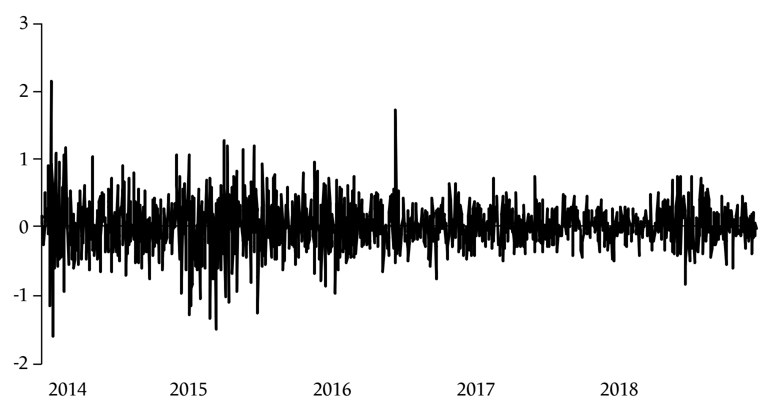

Figure 3
Daily EURCZK returns

Figure 4
The conditional variance estimated by the model and squared returns of EURPLN exchange rate presented on the background of regime 1 and 2 subperiods

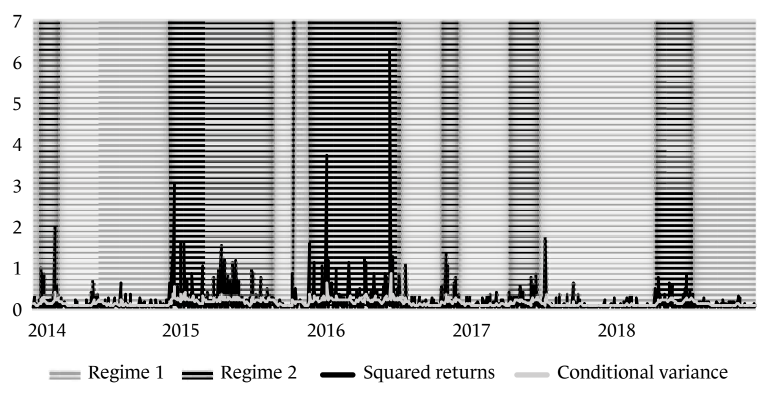

Figure 5
The conditional variance estimated by the model and squared returns of EURHUF exchange rate presented on the background of regime 1 and 2 subperiods

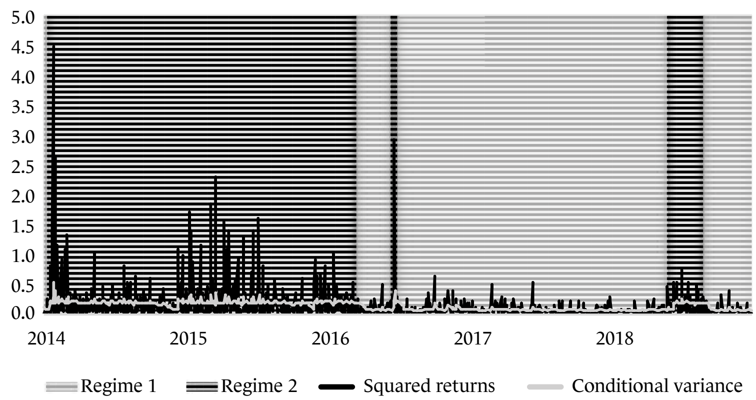

Figure 6
The conditional variance estimated by the model and squared returns of EURCZK exchange rate presented on the background of regime 1 and 2 subperiods

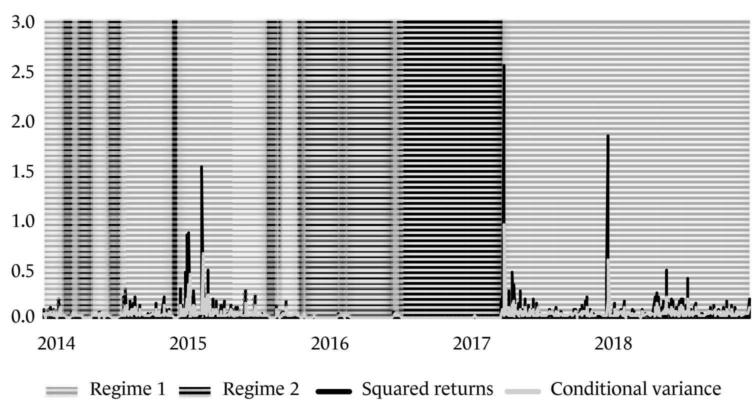

Table A.1
Periods of high and low volatility of exchange rates extracted from the models

	High volatility	**Low volatility**
EURPLN	22.01.2014–12.03.2014 15.12.2014–03.09.2015 21.10.2015–26.10.2015 01.12.2015–21.07.2016 31.10.2016–13.12.2016 19.04.2017–03.07.2017 23.04.2018–25.07.2018	06.01.2014–21.01.2014 13.03.2014–12.12.2014 04.09.2015–20.10.2015 27.10.2015–30.11.2015 22.07.2016–28.10.2016 14.12.2016–18.04.2017 04.07.2017–20.04.2018 26.07.2018–31.12.2018
EURHUF	14.01.2014–18.03.2016 16.06.2016–01.07.2016 29.05.2018–24.08.2018	06.01.2014–13.01.2014 21.03.2016–15.06.2016 04.07.2016–25.05.2018 27.08.2018–31.08.2018
EURCZK	06.01.2014–21.02.2014 17.03.2014–01.04.2014 08.05.2014–19.06.2014 21.07.2014–02.12.2014 16.12.2014–03.08.2015 26.08.2015–02.09.2015 08.09.2015–19.10.2015 22.10.2015–23.10.2015 03.11.2015–06.11.2015 04.02.2016–09.02.2016 22.02.2016–24.02.2016 22.06.2016–05.07.2016 30.03.2017–31.12.2018	24.02.2014–14.03.2014 02.04.2014–07.05.2014 20.06.2014–18.07.2014 03.12.2014–15.12.2014 04.08.2015–25.08.2015 03.09.2015–07.09.2015 20.10.2015–21.10.2015 26.10.2015–02.11.2015 09.11.2015–03.02.2016 10.02.2016–19.02.2016 25.02.2016–21.06.2016 06.07.2016–29.03.2017

Table A.2
Percentage of days of high volatility in each quarter for each exchange rate (%)

		EURPLN		
	Q1	**Q2**	**Q3**	**Q4**
2014	59.0	0.0	0.0	18.5
2015	100.0	100.0	71.2	40.0
2016	100.0	100.0	22.7	50.0
2017	0.0	81.3	1.5	0.0
2018	0.0	76.9	27.7	0.0
		EURHUF		
	Q1	**Q2**	**Q3**	**Q4**
2014	90.2	100.0	100.0	100.0
2015	100.0	100.0	100.0	100.0
2016	87.3	16.9	1.5	0.0
2017	0.0	0.0	0.0	0.0
2018	0.0	36.9	61.5	0.0
		EURCZK		
	Q1	**Q2**	**Q3**	**Q4**
2014	75.4	50.8	78.8	86.2
2015	100.0	100.0	71.2	29.2
2016	11.1	10.8	4.5	0.0
2017	3.1	100.0	100.0	100.0
2018	100.0	100.0	100.0	100.0

Identyfikacja zmian strukturalnych i zależności pomiędzy kursami walut środkowoeuropejskich za pomocą modeli przełącznikowych typu Markowa

Kursy walutowe mogą podlegać zmianom strukturalnym, doświadczając okresów wysokiej i niskiej zmienności (tzw. reżimów zmienności). Jest to szczególnie widoczne w przypadku kursów walut krajów rozwijających się. Celem artykułu jest identyfikacja okresów wysokiej i niskiej zmienności na rynkach walut z centralnej Europy za pomocą modelu przełącznikowego Hamiltona, porównanie uzyskanych szacunków zmienności i trwałości zidentyfikowanych reżimów zmienności dla poszczególnych kursów oraz sprawdzenie, czy pośród kursów istnieją zależności w występowaniu okresów wysokiej i niskiej zmienności. Wyniki oparte są na trzech szeregach czasowych kursów walut: EURPLN, EURCZK i EURHUF w okresie między 2014 a 2018 r. Wybór modelu przełącznikowego Hamiltona podyktowany był możliwością jego wykorzystania do wykrywania zmian strukturalnych w zmienności notowań.

Dla każdego z szeregów kursów walut środkowoeuropejskich względem euro oszacowany został model przełącznikowy Hamiltona, który dobrze odzwierciedla dynamikę tych kursów. Zaobserwowano, że kurs EURPLN doświadczył okresu wysokiej zmienności głównie w 2015 i 2016 r.; kurs EURHUF cechował się wysoką zmiennością między początkiem 2014 r. a marcem 2016 r., a kurs EURCZK był stosunkowo niestabilny w latach 2014, 2015, 2017 i 2018. Jednakże, porównując bezwarunkowe wariancje obu reżimów dla wszystkich modeli, to kurs EURCZK wykazuje się najniższą zmiennością spośród badanych kursów, a ponadto cechuje się większym prawdopodobieństwem pozostania w reżimie o niższej zmienności niż w reżimie o wyższej zmienności. Trwałość reżimów również różni się między oszacowanymi modelami. Dla kursu EURHUF przewidywany czas pozostawania w ramach danego reżimu oszacowany został na ok. 5–6 miesięcy, podczas gdy kursy EURPLN i EURCZK podlegają temu samemu reżimowi przez ok. 1–2 miesiące. Występowanie reżimów zmienności nie jest od siebie niezależne, co wskazuje na występowanie wspólnego czynnika wpływającego na zmienność kursów walut krajów środkowoeuropejskich wobec euro. Powiązanie między reżimami w stopniu co najmniej umiarkowanym widoczne jest dla kursów EURHUF i EURPLN, natomiast kurs EURCZK zachowuje się bardziej niezależnie.

Decydenci powinni zdawać sobie sprawę z możliwości wystąpienia zmian strukturalnych zachodzących w kursie walutowym w reakcji np. na nagłe zmiany w polityce pieniężnej, czego przykładem może być zmiana reżimu zmienności, która nastąpiła po decyzji Czeskiego Banku Narodowego w kwietniu 2017 r. Zmiany systemu walutowego to niejedyna przyczyna zmiany strukturalnej. Zmiany reżimu zmienności mogą również posłużyć do analizy wzorców widocznych w zachowaniu kursów walutowych. Wysoka częstotliwość zmian reżimu kursów EURPLN i EURCZK ujawnia podatność tych walut na „wahania nastroju" na rynku. Jest to czynnik utrudniający stabilizację kursu w ramach mechanizmu ERM II. Za czynnik ryzyka, szczególnie gdy ujawnia się to pod postacią zarażania na rynkach walutowych, można postrzegać wyniki testów niezależności, które potwierdzają pewien stopień integracji między walutami Europy Środkowej. Zależności określane jako *comovement* lub *interdependence* pomiędzy kursami EURPLN i EURHUF znajdują potwierdzenie w wynikach przeprowadzonych badań. Chociaż proces stabilizowania EURCZK powinien być łatwiejszy, nie można wykluczyć wystąpienia w przyszłości efektu wzrostu powiązań w zakresie zmienności (*volatility spillovers*) podczas kryzysu, jak sugerują Kočenda i Moravcová (2019).