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VOLATILITY REGIMES OF SELECTED CENTRAL EUROPEAN STOCK RETURNS: A MARKOV SWITCHING GARCH APPROACH

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Abstract. This paper investigates the weekly stock market data of the Hungarian stock index BUX, the Czech stock index PX and the Polish stock index WIG20 spanning from January 7, 2001 to April 18, 2021. The period of more than 20 years enabled to analyse the behaviour of returns and their volatility during both the calm as well as various crises/turmoil periods. Besides the traditional GARCH-type models (GARCH and GJR-GARCH) the two-regime Markov Switching GARCH-type models (MS-GARCH and MS-GJR-GARCH) were estimated in order to examine the volatility switches of the Central European transition stock markets. The *t*-distribution of error terms was used to capture the dynamics of analysed returns more precisely. The results proved high volatility persistence of individual markets which substantially differed across the both regimes. Furthermore, the GJR-GARCH and MS-GJR-GARCH models clearly confirmed the presence of the leverage effect. Consideration of the MS-GARCH-type models enabled to capture various volatility switches during the analysed period attributable mainly to the global financial crisis 2008–2009, to European debt crisis in 2011 and to the Covid-19 pandemic in 2020. Interesting results were received for the Czech market with the strong leverage effect indicating completely different specification of volatility regimes by the MS-GJR-GARCH model.

Keywords: stock returns, volatility, GARCH, GJR-GARCH, Markov-switching (MS), regime, MS-GARCH, MS-GJR-GARCH.

JEL Classification: C58, D53, G15, C22.

Introduction

During the last decades the financial markets in Central European transition countries[1] have undergone turbulent changes corresponding to the transition process from the centrally planned economies towards the market economies. A special milestone was the accession of

[1] This paper is focused on the financial markets in three Central European countries – Hungary, the Czech Republic and Poland.

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these countries to the European Union (EU) in 2004 and the gradual convergence of their financial markets with the developed EU markets. These events were likely to induce the potential effects on volatility of financial markets attracting the attention of investors and analysts. To describe and analyse the behaviour of a particular stock market over time, the stock indices and corresponding stock returns are usually used. The stock returns can be characterized by time-varying volatility and volatility clustering. To capture these stylized facts as well as to model the stock market dynamics, the well-known autoregressive conditional heteroscedasticity (ARCH) model of Engle (1982), its generalization to GARCH introduced by Bollerslev (1986) or various modifications of GARCH-type models, e.g., asymmetric EGARCH model (Nelson, 1991) or GJR-GARCH model (Glosten et al., 1993) are commonly used.

Furthermore, it is generally known, that the financial markets react very sensitively to information of various types, e.g., economic, political and health crises, changes in monetary or fiscal policy and natural disasters. The development of stock indices and of corresponding stock returns can thus change during some periods dramatically compared to its previous behaviour, which is termed a "structural break" or it may be a change lasting a certain period, after which the time series returns to the original behaviour or switches to another style of behaviour, usually known as a "regime-switching" (Brooks, 2008). In general, the regime-switching models can be used for modelling of return series and/or for volatility modelling.

However, as pointed out by many researchers (see, e.g., Ardia et al., 2019; Frömmel, 2010; Klaassen, 2002; Lamoureux & Lastrapes, 1990; Raihan, 2017; Živkov et al., 2020), the traditional GARCH-type models fail to capture the true variation in volatility in case of structural breaks in empirical time-series. In this case, due to the neglected regime changes, the sum of estimated GARCH parameters is close to one (or even exceeds one) which implies the possible non-stationarity of the volatility process, the overestimation of the volatility persistence and thus the GARCH model misspecification (Frömmel, 2010). To overcome the substantial upward bias in volatility persistence, the traditional GARCH-type model can be merged with the Markov switching (MS) model of Hamilton (1989). This combined model, called the Markov switching GARCH (MS-GARCH) model, enables to capture the structural break endogenously[2]. Cai (1994) and Hamilton and Susmel (1994) combined the ARCH model and the MS model. Another, more attractive specifications of the MS-GARCH model were presented by Gray (1996), Klaassen (2002) and Haas et al. (2004)[3]. Since the estimation of the MS-GARCH-type models is not trivial, the R software package MSGARCH (Ardia et al., 2019, 2020) based on the specification of Haas et al. (2004) provides nowadays a suitable option to estimate, to simulate and to forecast with the MS-GARCH-type models.

This paper investigates the volatility of selected Central European stock returns, namely the returns of the Hungarian stock index BUX, the Czech stock index PX and the Polish stock index WIG20 over the period January 7, 2001 – April 18, 2021. The aim of the paper is three-fold. Firstly, to compare the volatility persistence of traditional GARCH-type models (GARCH and GJR-GARCH) which ignore the possible structural changes during the

[2] Unlike other approaches based e.g., on the use of the dummy variables exogenously reflecting the changes in the volatility level.

[3] These specifications enable to avoid the problem of path-dependence with maximum likelihood.

analysed period with those of the two-regime MS-GARCH-type models (MS-GARCH and MS-GJR-GARCH) enabling varying volatility levels. Secondly, to assess the significance and magnitude of the leverage effect in analysed stock markets based both on the traditional GJR-GARCH as well as on the MS-GJR-GARCH models. Thirdly, to analyse whether the changes in the stock returns volatility regimes specified by MS-GARCH-type models (MS-GARCH and MS-GJR-GARCH) coincide with the commonly known crises/turmoil periods. The analysis is enriched by calculation of the five-step ahead conditional volatilities (April 25, 2021 – May 23, 2021) based on estimated MS-GARCH-type models to gain better insight into the behaviour of conditional volatilities of individual markets during the Covid-19 pandemic.

The importance of the research addressed in this paper is reflected by the selection of the Central European transition countries (Hungary, the Czech Republic and Poland) during the period of more than 20 years to investigate the structural breaks in stock returns volatility. The weekly data has covered e.g., the accession to the EU in May 2004, the periods before and after the global financial crisis of 2008 and the Covid-19 pandemic period, as well. This paper contributes to novelty of research by application of the modern econometric techniques enabling to capture not only the volatility clustering, but also the different behaviour of volatility in calm and crises periods for a set of largest Central European transition markets. Since various research papers has been published for several developed markets, the studies analysing the switching behaviour of volatility in Central European transition markets are very rare. Furthermore, the asymmetric GJR-GARCH and MS-GJR-GARCH models are used to describe the leverage effect in volatility. Imposing an asymmetry parameter in the density function considering the *t*-distribution of error terms, helps to capture the dynamics of analysed returns more precisely.

The paper is organised as follows. Introduction has offered the motivation to analyse the volatility of stock returns using the GARCH-type and MS-GARCH-type models, the formulation of the aims of the paper as well as the importance of the research. Section 1 includes literature review indicating previous research on the subject, Section 2 deals with the methodology applied in the research, Section 3 describes data and empirical results, Section 4 includes discussion, and the final section concludes with some ideas for further research.

1. Literature review

The popularity of analysing stock market volatility has been growing among analysts, scientists and investors. In recent years, along with the traditional single-regime GARCH-type models of e.g., Engle (1982), Bollerslev (1986), Nelson (1991) and Glosten et al. (1993), the regime-switching MS-GARCH-type models of e.g., Gray (1996), Klaassen (2002) and Haas et al. (2004) has become very attractive for the analysis and forecasting of volatility.

Marcucci (2005) compared a set of traditional GARCH-type models (GARCH, EGARCH and GJR-GARCH model) with the two regime MS-GARCH model in terms of their ability to forecast the volatility of S&P100. Frömmel (2010) investigated the volatility regimes in five Central and Eastern European countries' exchange rates and proved that while the estimation of a single-regime GARCH model led to variance processes which were almost non-stationary, the application of a MS-GARCH model provided substantially better results.

Rotta and Pereira (2016), using the regime-switching dynamic correlation approach, evaluated the contagion between developed and emerging stock market returns. Raihan (2017) evaluated the performances of MS-GARCH models in forecasting US inflation uncertainty. Ardia et al. (2018) presented a large-scale empirical study in order to analyse the forecasting performances of single-regime and MS-GARCH-type models. They found out the outperformance of the MS-GARCH models especially for stock return data. Spulbar et al. (2020) investigated the abnormal volatility transmission patterns between emerging and developed stock markets (including the Polish and Hungarian market). Estimation of symmetric and asymmetric GARCH-type models confirmed that all the analysed markets were highly volatile with the presence of leverage effect. Živkov et al. (2020) studied the volatility transmission between major agricultural futures using the MS-GARCH model and the Bayesian quantile regression framework. Silva (2021) used the MS autoregressive model to capture the regime changes in both the mean and variance of returns of Brazilian stock index and confirmed the regime changes corresponding to: the attacks from September 11, 2001, the moment of transition in Brazilian politics in 2002, the financial crisis of 2008 and the Covid-19 pandemic (2020/2021). The studies of Czech et al. (2020), Liu et al. (2020), Pyo (2021), Sema et al. (2021) and Zhang et al. (2021) analysed the impacts of the ongoing Covid-19 pandemic on the stock returns volatility.

With a special regard to the analysed group of Central European transition markets (Hungarian, Czech and Polish), the papers of Linne (2002), Bialkowski (2004), Moore and Wang (2007) and Kouretas and Syllignakis (2012) have to be mentioned. Linne (2002) examined the contagion effects of currency crises on several emerging stock markets in Central and Eastern Europe using the two-regime MS model. Bialkowski (2004) used the Markov regime-switching models to analyse the monthly returns of Central European stock indices as well as stock indices of selected Western European countries, confirming the different sensitivity of analysed stock indices to various international crises. Utilising the Markov regime-switching model proposed by Hamilton (1989), Moore and Wang (2007) analysed the volatility in the stock markets for the five new EU member states. In terms of their entry to the EU, the presented results pointed out to the tendency of stock markets to move from the high volatility regime to the low volatility regime indicating the stabilization of the analysed stock markets after the EU accession. Kouretas and Syllignakis (2012) investigated the volatility patterns of stock returns of the ten Central and Eastern European emerging capital markets based on the MS ARCH model. For the majority of markets, they confirmed higher volatility of stock returns during the crises periods. Furthermore, they proved the switch to the calm low volatility regime during the period preceding the accession to the EU in May 2004.

2. Methodology

Let us consider the closing prices of the stock market index P_t, then the corresponding continuously compounded return r_t is calculated as follows:

$$r_t = \ln\left(P_t\right) - \ln\left(P_{t-1}\right), \tag{1}$$

where the subscript t denotes time. The dynamics in the conditional mean, i.e., in return series, can be modelled through the estimation of the Autoregressive Moving Average – ARMA(p,q) models. The de-meaned time series (filtered returns), i.e., residuals of an ARMA(p,q) model, can be denoted as y_t, have a zero mean and are not serially correlated (Ardia et al., 2019). To capture the behaviour of the conditional variance h_t, the traditional GARCH-type models or MS-GARCH-type models can be estimated.

With regard to the empirical part of the paper, from a broad range of the traditional GARCH-type models only two models, namely the GARCH and the GJR-GARCH model will be presented.

The GARCH (1,1) model of Bollerslev (1986) is specified as follows:

$$h_t = \alpha_0 + \alpha_1 y_{t-1}^2 + \beta_1 h_{t-1}, \tag{2}$$

where the symbols α_0, α_1 and β_1 denote the unknown parameters. To ensure positivity of h_t, it must hold that $\alpha_0 > 0$, $\alpha_1 > 0$ and $\beta_1 \geq 0$. The covariance-stationarity is guaranteed if $\alpha_1 + \beta_1 < 1$, the unconditional volatility is defined as $\sigma = \sqrt{\alpha_0 / (1 - \alpha_1 - \beta_1)}$.

The GJR-GARCH model of Glosten et al. (1993) enables to capture the asymmetry in the conditional variance process, i.e., that good news and bad news have different effects on the conditional volatility. The GJR-GARCH (1,1) model is given by:

$$h_t = \alpha_0 + \left(\alpha_1 + \alpha_2 I\left[y_{t-1} < 0\right]\right) y_{t-1}^2 + \beta_1 h_{t-1}, \tag{3}$$

where $I[.]$ is an indicator function which takes the value one if $y_{t-1} < 0$ and zero otherwise. The conditions for positivity of the conditional variance are $\alpha_0 > 0$, $\alpha_1 > 0$, $\alpha_2 \geq 0$ and $\beta_1 \geq 0$. The condition for the covariance-stationarity is in case of symmetric distribution $\alpha_1 + 1/2\alpha_2 + \beta_1 < 1$ (for more details see e.g., Ardia et al., 2019). Unlike the GARCH model, the GJR-GARCH model is able to capture the empirically observed asymmetry, i.e., the fact that negative shocks at time $t-1$ have a higher impact on h_t than positive shocks of the same magnitude (known as a leverage effect). The unconditional volatility for the GJR-GARCH (1,1) model can be calculated as $\sigma = \sqrt{\alpha_0 / (1 - \alpha_1 - 1/2\alpha_2 - \beta_1)}$.

The standardized innovations z_t from models (2) and (3) are defined as:

$$z_t = \frac{y_t}{\sqrt{h_t}} \sim i.i.d.N\left(0,1\right). \tag{4}$$

Concerning the conditional distribution of the standardized innovations z_t (4), several alternative distributions can be considered. Besides the normal distribution, the Student's *t*-distribution and generalized error distribution (GED) are the most commonly used to model fat-tailed distributions (see e.g., Aktan et al., 2010; Marcucci, 2005). The skewed versions of these distributions can be used as well (Ardia et al., 2019).

As mentioned above, the traditional GARCH-type models often indicate the high volatility persistence of individual shocks. Klaassen (2002), among others, pointed out, that e.g., in case that the variance is high (low) but homoskedastic during some periods, a traditional GARCH-type model is not able to capture the persistence of such high and low periods and attributes the volatility persistence solely to the persistence of individual shocks. Allowing for the regime-switching in the conditional variance, the MS-GARCH-type model can be presented. Let us denote as I_{t-1} the information set at time $t-1$, then the MS-GARCH specification of Haas et al. (2004) is as follows (Ardia et al., 2019):

$$y_t \left| \left(s_t = k, I_{t-1} \right) \sim D\left(0, h_{k,t}, \epsilon_{\boldsymbol{k}} \right), \right. \tag{5}$$

where the symbol $D\left(0,h_{k,t},\epsilon_{\boldsymbol{k}}\right)$ denotes the continuous distribution with zero mean, time-varying conditional variance $h_{k,t}$ and additional shape parameters included in the vector $\epsilon_{\boldsymbol{k}}$. Random regime variable s_t assumes only integer values $\{1,2,\ldots,K\}$ and is governed by a first-order Markov process. A transition probability matrix $\mathbf{P}$ of dimension $K \times K$ contains transition probabilities $p_{ij} = P\left\{ s_t = j \middle| s_{t-1} = i \right\}$ giving the probability that the regime *i* (at time $t-1$) will be followed by the regime *j* (at time *t*). Since at any time, the variable should be in one of the K considered regimes, it should hold that $\sum_{j=1}^{K} p_{ij} = 1$ for $\forall i \in \{1,2,\ldots,K\}$. The expected duration in each regime $E\left(D_i\right)$ for $i \in \{1,2,\ldots,K\}$ indicating the average length of being in a specific regime can be calculated as follows (see e.g., Rotta & Pereira, 2016):

$$E\left(D_i\right) = \frac{1}{1-p_{ii}}. \tag{6}$$

Compared to traditional GARCH-type models, the MS-GARCH-type models thus enable to capture two main sources of volatility persistence, namely the within-regime persistence and the persistence of regimes (Klaassen, 2002; Raihan, 2017; Sajjad et al., 2008).

As pointed out by e.g., Haas and Paolella (2012), the applications of the MS-GARCH-type models are usually based on normal distribution. However, several research papers have shown (see e.g., Haas & Paolella, 2012; Klaassen, 2002) that a MS-GARCH model with normality assumption will identify the regime switches too often due to large innovation (outlier) in an otherwise low/high volatility regime. Allowing for leptokurtic components, like Student's *t*-distribution, will lead to better accommodation of such extreme realizations within a given regime, thus enhancing the stability of the regimes (Haas & Paolella, 2012; Klaassen, 2002).

Regarding the empirical part of the paper using the MS-GARCH specification of Haas et al. (2004), the conditional variances $h_{k,t}$ for $k = 1,2,\ldots,K$ can follow K separate GARCH-type models, i.e., the conditional variance of y_t is defined as a GARCH-type model as specified e.g., in (2) or (3). Furthermore, the conditional distribution can be specified differently for each regime, as well. For our analysis, we assume only two possible regimes, i.e., $K = 2$, indicating low volatility and high volatility regime and Student's *t*-distribution. Unconditional probabilities (stable probabilities) π_i of being in a specific regime ($i = 1,2$) can be thus obtained as follows:

$$\pi_i = \left(1 - p_{ii}\right) / \left(2 - p_{ii} - p_{jj}\right). \tag{7}$$

3. Data and empirical results

The analysed data set, retrieved from the web-page Stooq (2021), comprises weekly data of the three Central European transition markets' stock indices – the Hungarian stock index BUX, the Czech stock index PX and the Polish stock index WIG20[4] spanning from January

[4] For simplicity, the abbreviation "WIG" instead of "WIG20" will be used in the further text of the paper.

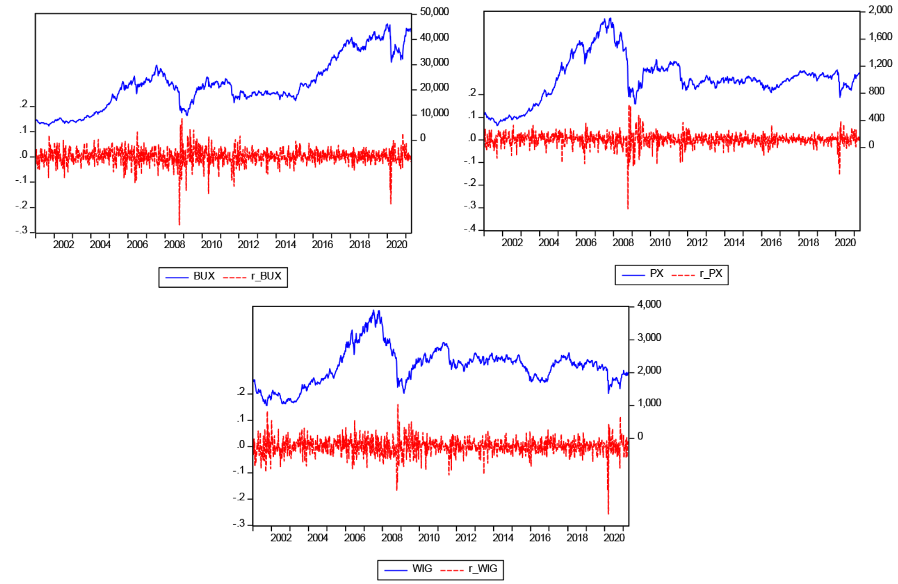


Figure 1. Development of stock indices and corresponding stock returns (prefix "r_")
(source: own calculations in EViews)

7, 2001 to April 18, 2021 (i.e., 1059 observations). Using the weekly data, both the nonsynchronous trading and the day-of-the-week effects were eliminated. The analysed period of more than 20 years provides an extensive information about the behaviour of analysed series during both the calm as well as various crises/turmoil periods, e.g., the accession to the EU in May 2004, the global financial crisis 2008–2009, the European debt crisis in 2011 and the Covid-19 pandemic in 2020. The whole analysis was done with the use of software EViews and R packages "rugarch" (Ghalanos, 2020) and "MSGARCH" (Ardia et al., 2020).

For each index, the continuously compounded returns were calculated based on formula (1) and are further denoted in the paper with the prefix "r_". The behaviour of analysed stock indices and corresponding stock returns is graphically illustrated in Figure 1. Since the behaviour of the stock indices was clearly non-stationary, the return series can be considered stationary[5]. All the return series showed a clear evidence of volatility clustering, i.e., that large (small) returns tend to be followed by another large (small) returns.

3.1. Behaviour of stock markets and some significant events

The begin of the new millennium on the financial markets was quite turbulent. The well-known burst of the dot.com bubble in March 2000 was followed by the stock market crash attributable to the attacks from September 11, 2001. In general, during the next few years 2002–2007 the financial markets have tended to grow. Furthermore, the first years of the new millennium in the Central European transition markets were linked to the ongoing process of financial liberalization and growing integration of financial markets both in the EU and

[5] The results are available from the author upon request.

the global context. A special milestone was the EU's eastern enlargement on May 1, 2004. However, the global financial crisis of 2008–2009 led to the significant crashes of the financial markets worldwide. Since during 2010 the behaviour on financial markets already showed signs of stabilization, the global positive trend of economic recovery slowed down in 2011. Significant turbulence in European financial markets was recorded mainly during the summer months (July, August) of 2011 due to the worsening debt crisis. Events in the financial markets continued to be quite turbulent during 2012 which could be attributable especially to the serious economic problems in Greece and Spain, speculations about the collapse of the euro area also emerged. In the second half of 2012, the situation calmed down slightly and the overall positive trend continued during 2013–2017, although it was accompanied by several risks associated with, for example, growing tensions in Ukraine, uncertainties related to the planned exit of the United Kingdom from the EU or uncertainties associated with the new US administration. However, during 2018 financial markets faced to several periods of declining asset prices and increased volatility. Although the growth of the global economy slowed markedly in 2019, financial markets mostly tended to grow. Most financial markets fell sharply during the first quarter of 2020 as a result of the outbreak and spread of the Covid-19 pandemic.

The behaviour of the analysed stock indices (BUX, PX and WIG) and stock returns, respectively mostly corresponded to the situation on financial markets described above (see Figure 1). Especially significant falls of all the analysed indices accompanied by high volatilities of corresponding stock returns were recorded during the global financial crisis period of 2008–2009, during the European debt crisis in 2011 and during the Covid-19 pandemic in the first months of 2020. Apart from the BUX index, the remaining two indices, i.e., PX and WIG, showed furthermore the falling values during 2015–2016. The global drop in stock markets of 2018 was clearly visible on the Hungarian and Polish market, far less on the Czech market.

3.2. Descriptive statistics and conditional mean equations

The descriptive statistics of the stock returns' data together with the results of normality testing (Jarque-Bera statistics with corresponding probability) are given in Table 1. The mean returns were around zero, the highest weekly percentage return was documented for the Hungarian market (0.16%), followed by the Czech and the Polish market with 0.08% and 0.01%, respectively. Concerning the standard deviations, the most volatile was the Polish market (3.20%) followed by the Hungarian (3.18%) and the Czech market (2.90%).

The sampling distributions of the analysed return series were negatively skewed with higher kurtosis than that of the normal distribution indicating fat-tailed returns. Both the highest degree of negatively skewed returns and the highest kurtosis were detected for the Czech market followed by the Hungarian market. From the analysed group of markets, the Polish market exhibited the lowest degree of negatively skewed returns and the lowest kurtosis. The non-normality of the distribution was confirmed by the values of the Jarque-Bera statistics. These facts pointed to the need to use the fat-tailed distribution, therefore both the GARCH-type and the MS-GARCH-type models were estimated using the maximum likelihood method based on the Student's t-distributed error assumption. As pointed out by e.g., Klaassen (2002) and Frömmel (2010), the t-distribution is quite popular in the estimation of GARCH-type models and is extra useful for regime-switching models since it can enhance the stability of the regimes.

Table 1. Descriptive statistics of stock returns (source: own calculations in EViews)

	r_BUX	r_PX	r_WIG
Mean	0.0016	0.0008	0.0001
Maximum	0.1516	0.1557	0.1601
Minimum	–0.2689	–0.3045	–0.2562
Std. Dev.	0.0318	0.0290	0.0320
Skewness	–1.0072	–1.4788	–0.7050
Kurtosis	10.8525	17.7325	9.3007
Jarque-Bera	2897.155	9953.823	1837.692
Probability	0.0000	0.0000	0.0000
Observations	1058	1058	1058

Since the returns of BUX (r_BUX) were serially uncorrelated, the values of the Ljung-Box Q-statistics strongly rejected the null hypothesis of no serial correlation for the remaining two return series, i.e., r_PX and r_WIG.[6] The conditional mean for r_BUX was thus supposed to be constant, the dynamics in the conditional mean of r_PX and r_WIG was described by the ARMA(6,4) and ARMA(3,3) model, respectively. The specifications of the conditional mean equation, the corresponding Ljung-Box Q-statistics for 12 and 200 lags, respectively as well as the ARCH LM diagnostics for 1 lag are gathered in Table 2. The presented results strongly indicated that while there was no serial correlation in the filtered returns (5% level of significance), the conditional heteroscedasticity was clearly confirmed.

Table 2. Conditional mean equations and residual diagnostics (source: own calculations in EViews)

	Model	Ljung-Box Q(12)	Ljung-Box Q(200)	ARCH LM(1)
r_BUX	–	19.821^{*}	218.89	37.655^{***}
r_PX	ARMA(6,4)	3.077	200.50	14.204^{***}
r_WIG	ARMA(3,3)	4.636	176.82	18.100^{***}

Note: In all tables of the paper the symbols ***, ** and * indicate the rejection of H_0 hypotheses at 1%, 5% and 10% level of significance, respectively.

The filtered returns (further denoted in the paper with the prefix "y_") were used for the estimation of the univariate GARCH (1,1) and GJR-GARCH (1,1) models assuming Student's t-distributed innovations.

6 The results are available from the author upon request.

3.3. Estimation of the GARCH-type models

The estimated parameters of models (2) and (3) for the analysed series together with the degrees of freedom (υ) of the standardized Student's *t*-distribution and the log-likelihood (LL) are included in Table 3. All the estimated parameters were statistically significant (with exception of α_1 parameter in case of GJR-GARCH model for y_PX). The estimates of the parameter α_2 in GJR-GARCH models for all markets were positive indicating the presence of the asymmetric effect of the past returns on the conditional volatility. The strongest volatility reaction on past negative returns was confirmed for the Hungarian market, followed by the Czech market. On the other hand, the Polish market proved significantly weaker leverage effect. As for the log-likelihood (LL) values, the asymmetric GJR-GARCH models exhibited higher values than the GARCH models in case of all analysed returns.

The assumption of covariance-stationarity for both the GARCH and GJR-GARCH model, i.e., $\alpha_1 + \beta_1 < 1$ and $\alpha_1 + 1/2\alpha_2 + \beta_1 < 1$, respectively, was fulfilled for all return series. Furthermore, these sums indicated quite high volatility persistence spanning between 0.9511 and 0.9660 in case of GARCH models and slightly lower values from 0.9371 to 0.9582 in case of GJR-GARCH models. The Czech market proved the lowest υ estimate, indicating considerably fat-tailed distribution, followed by the slightly higher values for the Hungarian and Polish market. The choice of the Student's *t*-distribution was thus confirmed to be appropriate, since the relatively small degrees of freedom parameters υ implied significant departure from normality (Ardia et al., 2019; Frömmel, 2010; Haas & Paolella, 2012; Klaassen, 2002; Raihan, 2017). Calculated unconditional volatilities σ were very close to their sample counterparts in Table 1, i.e. for both the GARCH and GJR-GARCH model the highest values of unconditional volatilities σ were detected for the Polish market followed by the Hungarian and the Czech market.

Table 3. Estimation results of GARCH (1,1)/GJR-GARCH (1,1) models with *t*-distribution (source: own calculations in R, package "rugarch")

	y_BUX	y_PX	y_WIG	y_BUX	y_PX	y_WIG
	GARCH (1,1) model			GJR-GARCH (1,1) model		
α_0	5.10^{-5**}	3.10^{-5**}	4.10^{-5**}	6.10^{-5**}	3.10^{-5**}	4.10^{-5**}
α_1	0.0984^{***}	0.1204^{***}	0.0829^{***}	0.0459^{*}	0.0501	0.0541^{**}
α_2	–	–	–	0.1130^{**}	0.0984^{***}	0.0582^{*}
β_1	0.8527^{***}	0.8456^{***}	0.8815^{***}	0.8348^{***}	0.8575^{***}	0.8751^{***}
υ	5.9125^{***}	5.5427^{***}	6.4864^{***}	6.2170^{***}	5.6908^{***}	6.7849^{***}
$\alpha_1 + \beta_1$	0.9511	0.9660	0.9643	–	–	–
$\alpha_1 + \beta_1 + 1/2\alpha_2$	–	–	–	0.9371	0.9569	0.9582
LL	2291.187	2451.012	2255.100	2295.630	2454.694	2256.976
σ	0.0303	0.0282	0.0313	0.0298	0.0259	0.0306

Note: Symbol LL denotes log-likelihood, υ indicates degrees of freedom of the *t*-distribution, σ is unconditional volatility.

3.4. Estimation of the MS-GARCH-type models

Table 4 provides estimation results for the MS-GARCH and MS-GJR-GARCH models, respectively. Both models were estimated under the assumption of Student's *t*-distributed innovations and two regimes – regime 1 (low volatility regime) and regime 2 (high volatility regime). The degrees of freedom parameters υ of the *t*-distribution were fixed across both regimes (see e.g., Haas & Paolella, 2012). The estimated values of υ between 6.6 and 14.2 confirmed that the modelled distributions had finite variance (as $\upsilon > 2$) and fatter tails than the normal distribution. Since the estimated parameters for the regime 1 were almost all statistically significant (with exception of two parameters for y_WIG, namely parameter α_{01} in MS-GARCH specification and parameter α_{11} in case of MS-GJR-GARCH specification), the parameters characterising the regime 2 were in case of Hungarian returns y_BUX for both model specifications statistically insignificant. As for regime 2, the statistically insignificant parameters were furthermore detected for Czech returns y_PX (α_{02} and α_{12} in MS-GARCH model, α_{12} in MS-GJR-GARCH model) and for Polish returns y_WIG (α_{12} in MS-GJR-GARCH model). The asymmetry parameters took different values in individual regimes. While the Hungarian market proved the stronger impact of bad news for the regime 1, both the Czech and Polish market showed significantly stronger reaction to bad news during the turbulent regime 2 as compared to the calm regime 1.

In general, the estimated parameters confirmed that the volatility process had a heterogeneous character across the two regimes. Firstly, the regimes differed concerning the unconditional volatility values. The unconditional volatilities for individual regimes $(i = 1,2)$ were calculated as $\sigma_i = \sqrt{\alpha_{0i} / (1 - \alpha_{1i} - \beta_i)}$ in case of MS-GARCH model and as $\sigma_i = \sqrt{\alpha_{0i} / (1 - \alpha_{1i} - 1/2\alpha_{2i} - \beta_i)}$ in case of MS-GJR-GARCH model. The within-regime volatility persistence of the MS-GARCH-type model is equivalent to the volatility persistence of traditional GARCH-type model. The results proved that the within-regime volatility persistence measured as $\alpha_{1i} + \beta_i$ and $\alpha_{1i} + 1/2\alpha_{2i} + \beta_i$, respectively was different across the regimes $(i = 1,2)$. Regime 1, denoted as a low volatility regime, was characterized by substantially higher within-regime volatility persistence in comparison to high volatility regime 2 for both model specifications. However, for both the Czech and the Polish market (the opposite is true for the Hungarian market), the immediate impact of a shock on the conditional volatility is higher in the high volatility regime than in the low volatility regime. This implies that the important source of volatility clustering in the high volatility regime could by attributable to the regime persistence not to the persistence of a single shock (Raihan, 2017).

The second source of volatility persistence, persistence of regimes, is given by transition probabilities p_{11} and p_{22}, i.e., by probabilities of staying in regime 1 and regime 2, respectively. Since the probabilities of staying in the low volatility regime (p_{11}) were for all returns (for both MS-GARCH-type models) more than 0.99 and statistically significant, the probabilities of staying in the high volatility regime $(p_{22} = 1 - p_{21})$ were mostly lower and in some cases even statistically insignificant. Hence, regime 1 has proved to be more persistent than regime 2 (the only exception was the Czech market in MS-GJR-GARCH model). The expected durations $E(D_i)$ are given by formula (6) and stable probabilities are defined by (7).

Table 4. Estimation results of MS-GARCH (1,1)/MS-GJR-GARCH (1,1) models with *t*-distribution, two regimes (source: own calculations in R, package "MSGARCH")

	y_BUX	y_PX	y_WIG	y_BUX	y_PX	y_WIG
	MS-GARCH (1,1) model			MS-GJR-GARCH (1,1) model		
	Regime 1 – low volatility regime					
α_{01}	2.10^{-5**}	2.10^{-5**}	3.10^{-5}	3.10^{-5**}	8.10^{-6**}	4.10^{-5*}
α_{11}	0.042^{*}	0.0833^{***}	0.0475^{**}	0.0327^{*}	1.10^{-6***}	2.10^{-6}
α_{21}	–	–	–	0.0634^{**}	0.1217^{***}	0.0636^{**}
β_1	0.9208^{***}	0.882^{***}	0.8915^{***}	0.883^{***}	0.912^{***}	0.8982^{***}
$\alpha_{11}+\beta_1$	0.9628	0.9653	0.9390	–	–	–
$\alpha_{11}+\beta_1$ $+1/2\alpha_{21}$	–	–	–	0.9474	0.9729	0.9300
	Regime 2 – high volatility regime					
α_{02}	0.0028	0.0012	0.0004^{*}	0.0035	0.0002^{**}	0.0004^{**}
α_{12}	0.0257	0.1184	0.1136^{**}	0.0022	5.10^{-5}	2.10^{-5}
α_{22}	–	–	–	0.0053	0.2542^{**}	0.1605^{**}
β_2	0.632	0.7099^{*}	0.6635^{***}	0.7422	0.607^{***}	0.6875^{***}
$\alpha_{12}+\beta_2$	0.6577	0.8283	0.7771	–	–	–
$\alpha_{12}+\beta_2$ $+1/2\alpha_{22}$	–	–	–	0.7471	0.7341	0.7678
υ	14.1967^{**}	6.9296^{***}	7.5325^{***}	12.4158^{***}	6.602^{***}	8.8161^{***}
p_{11}	0.9905^{***}	0.995^{***}	0.9951^{***}	0.9934^{***}	0.9923^{***}	0.9932^{***}
p_{21}	0.2692^{*}	0.1527^{*}	0.008	0.4667^{**}	0.005	0.0093^{*}
LL	2293.078	2449.687	2256.596	2295.768	2461.900	2261.006
σ_1	0.0233	0.0230	0.0244	0.0250	0.0170	0.0228
σ_2	0.0905	0.0820	0.0409	0.1171	0.0271	0.0396
π_1	0.9661	0.9685	0.6235	0.986	0.3931	0.5801
π_2	0.0339	0.0315	0.3765	0.014	0.6069	0.4199
$E(D_1)$	105.2632	200	204.0816	151.5152	129.8701	147.0588
$E(D_2)$	3.7147	6.5488	125	2.1427	200	107.5269

Note: The degree of freedom parameter υ of the *t*-distribution is fixed across the regimes; p_{11} and p_{21} – transition probabilities; LL – log-likelihood; σ_1 and σ_2 – unconditional volatilities; π_1 and π_2 – stable probabilities; $E(D_1)$ and $E(D_2)$ – expected durations.

As for the Hungarian returns y_BUX and the Polish returns y_WIG, both the stable probabilities of being in the low volatility regime 1 and the expected durations of regime 1 were higher in comparison to the values for the high volatility regime 2. In case of the Czech returns y_PX the estimation of the MS-GARCH and MS-GJR-GARCH model led to different results. Based on the MS-GARCH model the stable probabilities clearly indicated the substantially higher probability of the low volatility regime 1 of more than 0.96 and expected duration of 200 weeks compared to the probability of around 0.03 and expected duration of 6.5 weeks in case of regime 2. However, the MS-GJR-GARCH estimation results (taking into account the significant leverage effect) indicated higher stable probability of the high volatility regime 2 of around 0.60 and expected duration of 200 weeks, while the probability of regime 1 was of around 0.40 and expected duration of almost 130 weeks.

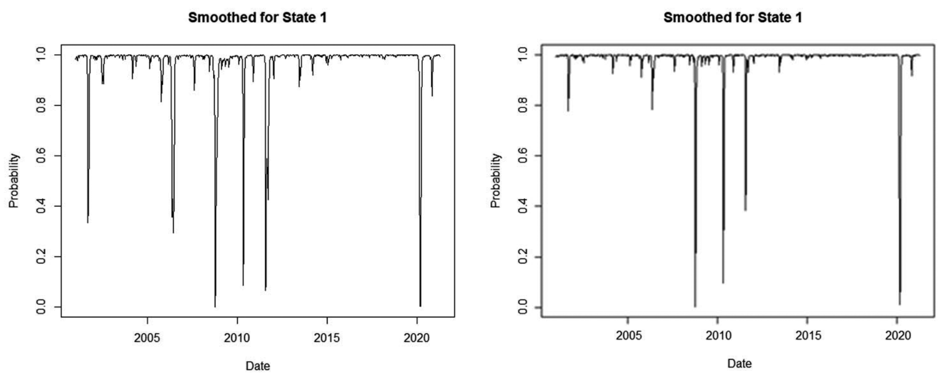
The values of log-likelihood (LL) can offer an initial view to assess whether the regime persistence is a considerable source of volatility persistence (see, e.g., Klaassen, 2002). For the Hungarian and the Polish markets the log-likelihoods corresponding to MS-GARCH-type models (see Table 4) were higher than their traditional GARCH-type model counterparts (see Table 3). The same holds for the Czech market, but only for the asymmetric MS-GJR-GARCH vs. GJR-GARCH model. However, the log-likelihood was lower for the MS-GARCH model than for the traditional GARCH model in this market. Overall, the comparison of log-likelihoods showed that the consideration of regimes can help to capture the volatility persistence.

Figure 2 shows the smoothed probabilities for the low volatility regime 1 of the MS-GARCH and MS-GJR-GARCH model, respectively. The presented results indicate different characteristics of individual markets.

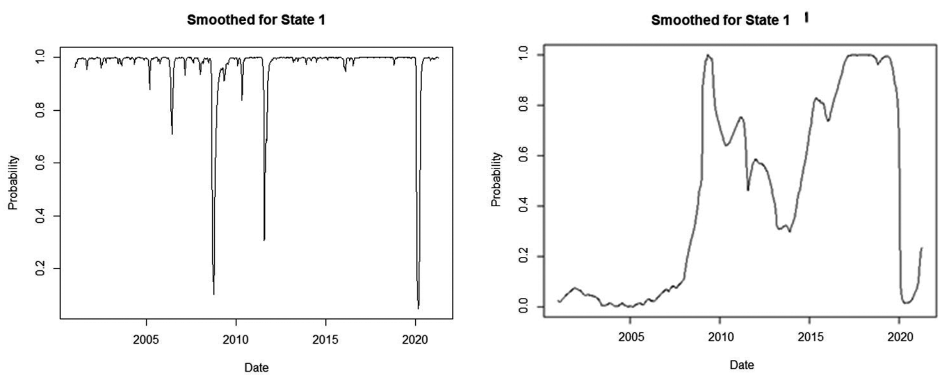
In case of Hungary the both MS-GARCH-type models provided similar results indicating that majority of time the market was in a calm period with several short sudden switches to the high volatility regime corresponding mostly to the commonly declared turmoil periods like e.g., the global financial crisis (October 2008), flash crash attributable to automated algorithmic trades (May 2010), the European debt crisis (summer 2011) and the Covid-19 pandemic (March 2020). However, based on the MS-GARCH model, the two more switches to the high volatility regime were detected – the first one attributable to the attacks from September 11, 2001 and the second one reflecting the politically and financially complicated situation of 2006 in Hungary.

The analysis of the smoothed probabilities' behaviour for the Polish returns showed that these did not move too frequently between the two regimes and spent most of time either close to 0 or close to 1. The initial period 2001–2002 (reflecting the attacks from September 11, 2001, the parliamentary elections and the short decline in the GDP growth) belonged to the high volatility regime. However, according to both models, the Polish market was more than a half of analysed time period in a low volatility regime 1 with further switches to the high volatility regime 2: during the second half of 2003 following the referendum on the EU accession in Poland (only MS-GJR-GARCH model), during approximately 2006–2009 corresponding to the period preceding the global financial crisis and financial crisis period and during an outbreak of the Covid-19 pandemic in March 2020.

y_BUX



y_PX



y_WIG

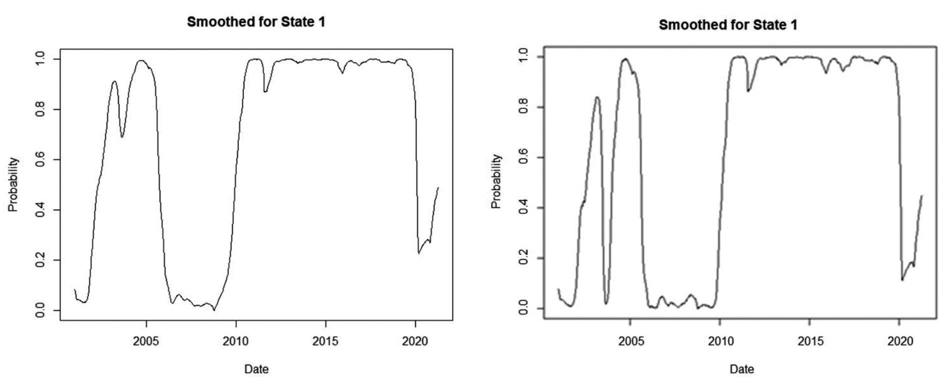


Figure 2. Smoothed probabilities for the regime 1:
MS-GARCH (1,1) models with two regimes (left) and MS-GJR-GARCH (1,1)
with two regimes (right) (source: own calculations in R, package "MSGARCH")

The Czech market is a special case in our sample. The smoothed probabilities of MS-GARCH model detected sudden volatility switches from the low volatility to high volatility regime in October 2008, in summer 2011 and in March 2020 corresponding to the global financial crisis, the European debt crisis and to the Covid-19 pandemic outbreak, respectively. However, the smoothed probabilities of MS-GJR-GARCH model proved a completely different behaviour. Since the periods 2001–2008 and March 2020 (the Covid-19 pandemic outbreak) clearly belonged to the high-volatility regime, affinity for this regime was more likely for periods including summer 2011 and November 2012-summer 2014 (the outbreak and spread of a European debt crisis), as well.

To illustrate the behaviour of conditional volatilities of individual markets during the next 5 weeks of the Covid-19 pandemic (April 25, 2021 – May 23, 2021), the estimated MS-GARCH (1,1) and MS-GJR-GARCH (1,1) models, respectively were used to calculate the five-step ahead conditional volatilities (see Table 5). For both model specifications the forecasted values indicated the highest conditional volatility of the Polish market followed by the Hungarian and the Czech market.

Table 5. Five-step ahead conditional volatilities of MS-GARCH (1,1)/MS-GJR-GARCH (1,1) models (source: own calculations in R, package "MSGARCH")

	y_BUX	y_PX	y_WIG	y_BUX	y_PX	y_WIG
	MS-GARCH (1,1) model			MS-GJR-GARCH (1,1) model		
April 25, 2021	0.0249	0.0199	0.0309	0.0234	0.0211	0.0310
May 2, 2021	0.0258	0.0205	0.0313	0.0252	0.0219	0.0313
May 9, 2021	0.0275	0.0219	0.0327	0.0264	0.0231	0.0324
May 16, 2021	0.0270	0.0216	0.0328	0.0254	0.0235	0.0324
May 23, 2021	0.0278	0.0222	0.0337	0.0265	0.0245	0.0333

4. Discussion

In accordance with many other researchers (see e.g., Ahmed et al., 2018; Aktan et al., 2010; Frömmel, 2010; Lamoureux & Lastrapes, 1990; Raihan, 2017; Rotta & Pereira, 2016; Spulbar et al., 2020) it was proved that the financial markets under consideration were highly volatile indicating the volatility persistence from 0.9511 to 0.9660 (GARCH model) and from 0.9371 to 0.9582 (GJR-GARCH model).

Taking into account the occurrence of possible structural changes, turmoil and crises, the MS-GARCH and MS-GJR-GARCH models enabled to capture the varying volatility levels. Supposing two possible volatility regimes, the empirical results showed that the low volatility regime (regime 1) reported substantially higher within-regime volatility persistence than a high volatility regime (regime 2) for all the MS-GARCH and MS-GJR-GARCH models, respectively. Our results are in line with those of e.g., Frömmel (2010) for Romanian leu and Raihan (2017) who confirmed higher within-regime volatility persistence during the calm low volatility regime which is, on the other hand, in contrast to the findings of e.g., Ardia et al. (2019), Klaassen (2002), Marcucci (2005) and Sajjad et al. (2008) who proved higher within-regime volatility persistence in the high volatility regime. With regard to the persistence of regimes, our results proved mostly higher regime persistence of regime 1 (more than 0.99), whereas the probabilities of staying in regime 2 were mostly lower and in some cases even statistically insignificant. The behaviour of smoothed probabilities has shown that the regimes were relatively stable with low uncertainty about the specification of a particular regime in individual weeks (Rotta & Pereira, 2016). In accordance with e.g., Klaassen (2002) and Frömmel (2010), our results confirmed that the consideration of volatility regimes enabled to assess different volatility persistence in individual regimes.

Concerning the second aim of the paper, the leverage effect was proved to be significant in case of all stock return series for both the GJR-GARCH and MS-GJR-GARCH models. Since the traditional GJR-GARCH models indicated the highest magnitude of the asymmetry for the Hungarian market followed by the Czech and Polish markets, the MS-GJR-GARCH models, enabling to capture different impact of bad news in individual regimes, provided diverse results. Cleary highest asymmetry in both regimes was proved for the Czech market, higher asymmetry in high volatility regime 2 in comparison to regime 1 was exhibited for the Polish market, as well. As for the regime 1, the Hungarian market reported the asymmetry parameter of almost identical magnitude as the Polish market, but substantially lower and insignificant asymmetry for the regime 2. Furthermore, the use of the *t*-distribution enabled to capture the higher kurtosis and heavy tails of the distribution and prevented the excessive switching between regimes (Frömmel, 2010; Klaassen, 2002). Our results confirming the presence of the leverage effect correspond to the findings of e.g., Rotta and Pereira (2016) and Spulbar et al. (2020).

Thirdly, we found coincidence of the regime-switching with the commonly known crises/turmoil periods, but the results differ across analysed countries (Kouretas & Syllignakis, 2012; Moore & Wang, 2007). The Hungarian and the Polish market tended to be most of the time in the low volatility regime 1 with no significant differences between estimation results of MS-GARCH model and MS-GJR-GARCH model, respectively. On the other hand, unlike Hungary and Poland, the differences between the MS-GARCH and MS-GJR-GARCH models were pronounced for the Czech market. As for the MS-GARCH model, the changes in the volatility regimes partially resembled the Hungarian market, however indicating only 3 switches to the high volatility regime (global financial crisis in October 2008, European debt crisis in summer 2011 and outbreak of the Covid-19 pandemic in March 2020). The MS-GJR-GARCH model captured the significantly asymmetric reaction of volatility to positive and negative shocks, but delivered completely different results regarding the regime switching indicating that the Czech market spent majority of time in the high volatility regime 2.

Conclusions

The objective of this research was to study the volatility of selected Central European transition stock markets (Hungary, the Czech Republic and Poland) using the weekly data of the main stock indices, i.e., BUX, PX and WIG20, respectively during the period of more than 20 years. The methodology of traditional GARCH-type and Markov Switching GARCH-type models (supposing the *t*-distributed errors) was selected in order to ensure the fulfilment of the formulated aims. The presented paper can thus contribute to the scarce research dealing with the volatility switches of Central European transition stock markets.

Our results clearly confirmed that the MS-GARCH-type models generalize the traditional GARCH-type models by enabling the flexibility of the volatility process. In addition to country-specific results, some general conclusions can be drawn. The estimated MS-GARCH-type models successfully identify the breakpoints in stock returns volatilities, namely the global financial crisis of 2008, the European debt crisis in 2011 and the Covid-19 pandemic of 2020. On the other hand, our models did not show switching of volatility regimes associated with the EU accession in May 2004 (apart from estimation of MS-GJR-GARCH model for Poland). Furthermore, the five-step ahead conditional volatilities calculated for both estimated MS-GARCH-type models indicated the highest conditional volatility of the Polish market followed by the Hungarian and the Czech market.

Due to the presence of the significant leverage effect proved by all the three analysed stock markets and due to the interesting results in terms of switching volatility regimes received for the Czech market, for the future research it seems to be challenging to study both the within-regime volatility persistence and regime persistence of different MS-GARCH-type models for a broad group of transition markets including the country-specific economic settings. Furthermore, since one of the limitations of our study is the use of MS models only for modelling of the volatility process, for the future research, it seems to be promising to deal with the estimation of full MS models enabling both the regime-switching mean and variance. Consideration of other alternative distributions (like e.g., skewed Student's *t*, GED and skewed GED) could shed further light on dynamics of stock returns and their volatility.

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The author declares that there is no conflict of interest.

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