3. Volatility Clustering, Leverage Effects and Risk-return Trade-off in the Selected Stock Markets in the CEE Countries

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Abstract

This research is focused on volatility and leverage effects in emerging markets of widely understood region of Central and Eastern Europe (i.e., for example, Russia is included in the analysed sample). The considered period covers the years 2005-2015. Methodology is based on generalized autoregressive conditional heteroscedastic models (GARCH). In particular, GARCH-M and asymmetric T-GARCH, E-GARCH, GJR-GARCH and APARCH models with generalized error distribution are estimated and discussed. If the currents finding are consistent with some of the previous papers, there are still also some outcomes inconsistent with other researches. Herein, also stability tests are performed – a problem not often found in reports from GARCH analysis of CEE. The results show that GARCH-M, T-GARCH and E-GARCH are the best models with respect to passing diagnostic tests. Moreover, current findings strongly support the hypothesis of the presence of leverage effect or negative risk-return trade-off in certain CEE countries. The assumption of generalised error distributions occurs to be reasonable for the majority of the analysed countries.

Keywords: emerging markets, GARCH, stock returns
JEL Classification: C22, G11, G17

Introduction

The financial time series are usually characterized by volatility clustering and leptokurtocity. The first effect is a tendency of grouping periods of higher and lower volatility. The second effect is that the distribution of a sample exhibits heavy tails and a peak around the mean value. As a result, these time series can be modelled by a suitable GARCH model (Bollerslev, 1986). It should be noticed that GARCH models are just one of possible methods of capturing a time-varying conditional variance; yet, very popular and useful.

Black (1976) was amongst the first who suggested that prices are negatively correlated with volatility. Although, there are various theoretical explanations of this empirical effect, its presence is well-recorded by numerous practically oriented researches (Ait-Sahalia *et al.*,

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2013). However, the simple GARCH model assumes that positive and negative shocks have the same impact on volatility. This is not always desired. Indeed, Nelson (1991) argued that there could be a negative correlation between the present returns and the future volatility and this is a serious drawback of the simple (symmetric) GARCH type models.

His considerations started a development of asymmetric generalizations of GARCH model (Ding *et al*., 1993; Glosten *et al*., 1993; Zakoian, 1994). Indeed, nowadays it is usually called "an asymmetric leverage effect" that volatility rises after large price declines, whereas for upward price movements this effect is smaller. This observation is also included amongst so-called "stylized facts" (Bekaret & Wu, 2000).

The mentioned properties were numerously studied for the developed markets, but in case of Central and Eastern Europe (CEE) there is not so much studies in this direction. On the other hand, emerging markets are usually characterised by the higher average returns in relation to volatility, but with the higher volatility itself. Also, in many cases simple GARCH(1,1) model is enough to describe the data. Moreover, these markets are known to be loosely correlated with the developed markets (Arora *et al*., 2009; Bekaert & Wu, 2000; Girard & Biswas, 2007; Selçuk, 2005).

Therefore, it is sensible to consider certain stock market indices from CEE countries. In particular, in this paper 14 time series were selected and for each one a suitable GARCH type model, available to capture the negative correlation between returns and volatility, was estimated and diagnosed. It seems that there is no similar research covering many countries from CEE in the recent period. Moreover, herein the period before and after the recent global financial crisis is covered. Therefore, the stability of the estimated parameters was checked.

Literature Review

Of course, the behaviour of stock returns is very important in risk estimation and risk management, asset pricing, portfolio selection, etc. For these GARCH methods are applied very often due to their usefulness (Thupayagale, 2010).

The CEE countries (herein understood in the very broad sense) consists of economies at different transition stages. For example, in the terminology of IMF, the Baltic countries, Czech Republic and Slovakia are "advanced economies", whereas the other CEE countries are described as "developing economies". In this context it is also interesting to notice the observation of Syriopoulos (2006) that the Visegrad countries seem to be more linked with developed economies than their geographical neighbours.

Achraf *et al*. (2013) found a high transmission of volatility of the US market to developed stock markets. Similar conclusions were given by Michelfelder & Pandya (2005), who found that emerging markets have higher volatility and that US market shocks are rapidly transmitted to the emerging markets. Nevertheless, in case of Asia, Worthington and Higgs (2004) found that mean spillovers from the developed to the emerging markets are not homogeneous. Generally, the strength of interactions between developed and emerging markets is still debatable (Sawa & Aslanidis, 2010).

For example, in case of the Polish, Hungarian, US and German stock exchanges only a weak linkage was found by Li & Majerowska (2008). As a result, investors from the developed markets were advised to diverse their portfolio with the stocks from the emerging markets.

The first comparative study of European transition economies focused on the asymmetric leverage effect, using daily indices, were done by Poshakwale & Murinde (2001). Yet, they concluded that no asymmetric volatility effects are found for most of the markets. Moreover, that GARCH-M model does not explain the expected returns in any of the analysed markets. However, they agreed that GARCH model suitable explains heteroskedasticity in volatility. On the other hand, Kasch-Haroutounian & Price (2001) suggested some weak asymmetric effects for the Visegrad countries.

It should be noticed that GARCH-M model has a useful property of containing the "risk premium" parameter. At first sight, it is expected to be positive, as the increase in volatility (risk) should be compensated by higher returns (premia). However, the leverage effect means that it is rather negative. Indeed, such a thing has been observed in various situations. Indeed, emerging markets are amongst them (Floros, 2008).

For the exchange rates of the selected Asian and Latin American countries Sandoval (2006) stated that, from the practical point of view, asymmetric GARCH models should not be preferred over symmetric ones. However, Harrison and Moore (2012) suggested that asymmetric GARCH models should outperform the symmetric ones in case of CEE countries, but their sample comes from less countries than the one used in this paper. On the other hand, their sample covers almost 18 years. Asymmetric models were also favoured in the study of emerging Asian markets (Daal *et al*., 2007).

Patev & Kanaryan (2006) found that the response of volatility from the good and the bad news is asymmetric in CEE, indeed. However, their research was based on a sample before EU accession, which can strongly influence their outcomes (Kouretas & Syllignakis, 2012). Secondly, they analysed not particular indices, but the Central European Stock Index. However, they found that asymmetric GARCH models with non-normal distribution of residuals are preferred, as well as, that the asymmetry increases in crises periods.

Vosvrda & Zikes (2004) found GARCH model to be very useful for certain Central European countries. Moreover, they reported non-normality of residuals also. Yet, quite contrary results were reported by Nyberg (2012), who used GARCH-M model. However, he extended the original model and quite differently treated certain periods of the business cycle.

The Romanian stock market in a more general context was analysed by Azam *et al*. (2014), Gabriel (2012) and Miron & Tudor (2010). South East European countries were recently analysed by, for example, Cerović *et al*. (2015) and Zikovic (2008). If out of the CEE countries, the Polish, Czech and Romanian markets were analysed by more researches, there are still few analyses on the Baltic region (Aktan, *et al*., 2010; Teresine, 2009).

Recently, Okičić (2014) analysed 13 indices from certain CEE countries. She found some confirmation that GARCH models suitably describe volatility of stock returns and that there exists the leverage effect in the selected countries. The presence of a long memory in the returns in majority of CEE countries was found by Necula & Radu (2012).

So, when applicability of GARCH models is obvious, there is also a problem of choosing the suitable number of lags in a GARCH variance equation. Actually, GARCH(1,1) seems to be enough to start the analysis (Hansen & Lunde, 2005). However, Uğurlu (2014) found that for the Romanian stock exchange GARCH(1,2) specification could be more suitable in certain cases[2].

Methodology

The theoretical part is based on Francq & Zakoian (2010), Poon (2005) and Zivot (2009). Computations were done in R with "rugarch" package (R Core Team, 2015; Ghalanos,

2 *Indeed, a similar situation occurred in the current research, however for another stock market.*

2014), which allows for a maximum likelihood estimation of a GARCH model. The data were obtained from Stooq (2015). The following stock market indices (resp. countries) were included in the sample: BET (Romania), BUX (Hungary), PX (Czech Republic), SAX (Slovakia), SOFIX (Bulgaria), UX (Ukraine), RTS (Russia), WIG20 (Poland), OMXR (Latvia), OMXT (Estonia), OMXV (Lithuania), CROBEX (Croatia), BIRS (Serbia), MONEX (Montenegro). First, daily data beginning on 1/7/05 and ending on 6/7/15 were considered.

The sample was chosen prior to cover relatively many countries from CEE and, simultaneously, a long period. The covered period was required to be exactly the same for all indices. Moreover, if possible, a blue chip index was preferred over an all-stock one. Finally, only, OMXR, OMXT, OMXV and MONEX are all-share indices.

Unfortunately, there were serious optimization problems for estimating GARCH models for daily logarithmic returns in some countries. Therefore, data were aggregated to weekly series and then weekly logarithmic returns were analysed. It did not lead to any significant weakening of the ARCH effect. As a result, the sample consisted of 522 observations for each time series (Figure 1). Moreover, such an aggregation reduces the short-term "noise". In case of the chosen countries, it also allows to obtain a consistent data for the whole period. Indeed, weekly data were already used in relevant GARCH-based researches (Joy, 2011; Mohammadi & Su, 2010; Guo & Neely, 2008; Bali & Guirguis, 2007; Worthington & Higgs, 2004). Actually, Ng & Lam (2006) discussed certain problems with samples with less than 700 observations, but they focused only on GARCH(1,1) model. Similarly, Hwang & Valls Pereira (2006) recommended using samples with more than 500 observations. In fact, our sample fulfils their requirement; but still they discussed just GARCH(1,1) model which has more narrow conditions than, for example, GJR-GARCH or E-GARCH.

In particular, t indexes every 5 session day and It denotes the value of the index at the end of day t. Then, GARCH models were estimated for the variable xt defined in the following way:

$$x_t = \ln (I_t / I_{t-1}) \tag{1}$$

For each time series GARCH-M, T-GARCH, GJR-GARCH, E-GARCH and APARCH models were estimated (Rodriguez & Ruiz, 2012). It is understood that x_t follows GARCH(p,q) process, if

$$x_t = \mu + e_t , \tag{2}$$

where: $e_t = u_t \sqrt{h_t}$ and u_t follows the generalized normal distribution and

$$h_t = \omega + \alpha_1 \cdot (e_{t-1})^2 + \ldots + \alpha_p \cdot (e_{t-p})^2 + \beta_1 \cdot h_{t-1} + \ldots + \beta_q \cdot h_{t-q} . \tag{3}$$

Usually, it is assumed that u_t follows the standard normal distribution. However, basing on the descriptive statistics (Table 1) it is clear that significant deviation emerges in the concentration of values around mean. Moreover, the tail behaviour is of a particular interest herein.

Formally, it is said that u_t follows the generalized normal distribution, if its density is given by

$$s \cdot \exp (- 0.5 \cdot | (x - \alpha) / \beta |^s) / [2^{1+1/s} \cdot \beta \cdot \Gamma (1 / s)] , \tag{4}$$

where: α, β and s are respectively parameters of the location, scale and shape. Naturally, the shape parameter is of the main interest herein. Generally, the parameter α is the mean (and also mode and median). If s = 2, the normal distribution with mean α and standard deviation β is obtained. For s = 1 – the Laplace distribution.

Figure 1

Weekly Logarithmic Returns

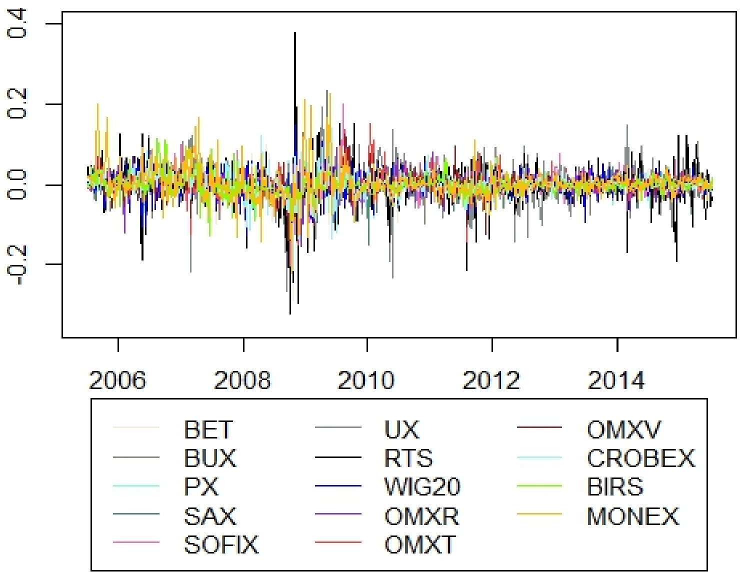

Table 1

Descriptive Statistics of the Sample

	mean	std. dev.	min	max	skew	kurtosis
BET	0.000747	0.039210	-0.286943	0.141151	-1.204087	8.79435
BUX	0.000228	0.038295	-0.193454	0.277915	0.114287	7.28649
PX	-0.000417	0.034055	-0.211010	0.253044	-0.260899	9.97526
SAX	-0.001004	0.022446	-0.151974	0.138330	-0.806696	8.94778
SOFIX	-0.000802	0.032857	-0.254065	0.200027	-1.283690	14.07398
UX	0.000616	0.053057	-0.264265	0.275613	-0.243931	4.94604
RTS	0.000426	0.056598	-0.320821	0.378713	-0.638394	8.04643
WIG20	0.000161	0.033955	-0.128707	0.146839	-0.430256	2.15191
OMXR	-0.000185	0.027088	-0.155612	0.095627	-0.965206	5.16333
OMXT	0.000657	0.029432	-0.176048	0.149631	-0.652433	7.31996
OMXV	0.000374	0.027478	-0.158734	0.125252	-0.971721	7.67342
CROBEX	-0.000052	0.032165	-0.213584	0.138215	-1.054801	7.20731
BIRS	-0.000900	0.025349	-0.129894	0.112456	0.350561	4.66559
MONEX	0.001805	0.041629	-0.222426	0.224443	0.843993	7.31389

BET (Romania), BUX (Hungary), PX (Czech Republic), SAX (Slovakia), SOFIX (Bulgaria), UX (Ukraine), RTS (Russia), WIG20 (Poland), OMXR (Latvia), OMXT (Estonia), OMXV (Lithuania), CROBEX (Croatia), BIRS (Serbia), MONEX (Montenegro).

Except just one case, GARCH(1,1) was enough for the scope of this research. The models used in this research are modifications of the base GARCH model. The difference is in the variance equations. Models are presented in Table 2. Of course, APARCH class includes GJR-GARCH and T-GARCH.

Table 2

Models Used

GARCH	$x_t = \mu + \sigma \cdot h_t + e_t$, $h_t = \omega + \alpha_1 \cdot (e_{t-1})^2 + \beta_1 \cdot h_{t-1}$.
GARCH-M	$x_t = \mu + \sigma \cdot h_t + e_t$, $h_t = \omega + \alpha_1 \cdot (e_{t-1})^2 + \beta_1 \cdot h_{t-1}$. the parameter σ represents “risk premium”.
T-GARCH	$x_t = \mu + \sigma \cdot h_t + e_t$, $\sqrt{h_t} = \omega + \alpha_1 \cdot \sqrt{h_{t-1}} \cdot (\mid z_{t-1} \mid - \eta_1 \cdot z_{t-1}) + \beta_1 \cdot \sqrt{h_{t-1}}$, where $z_t = e_t / \sqrt{h_t}$.
GJR-GARCH	$x_t = \mu + \sigma \cdot h_t + e_t$, $\ln (h_t) = \omega + \alpha_1 \cdot (e_{t-1})^2 + \gamma_1 \cdot I_{t-1} \cdot (e_{t-1})^2 + \beta_1 \cdot \ln (h_{t-1})$, where $I_{t-1} = 1$ if $e_{t-1} < 0$ and $I_{t-1} = 0$ otherwise.
GJR-GARCH(2,1)	$x_t = \mu + \sigma \cdot h_t + e_t$, $\ln (h_t) = \omega + \alpha_1 \cdot (e_{t-1})^2 + \alpha_2 \cdot (e_{t-2})^2 + \gamma_1 \cdot I_{t-1} \cdot (e_{t-1})^2 + \gamma_2 \cdot I_{t-2} \cdot (e_{t-2})^2 + \beta_1 \cdot \ln (h_{t-1})$, with $I_{t-1} = 1$ if $e_{t-1} < 0$ and $I_{t-1} = 0$ otherwise, and $I_{t-2} = 1$ if $e_{t-2} < 0$ and $I_{t-2} = 0$ otherwise.
E-GARCH	$x_t = \mu + \sigma \cdot h_t + e_t$, $\ln (h_t) = \omega + \alpha_1 \cdot z_{t-1} + \gamma_1 \cdot (\mid z_{t-1} \mid - E \mid z_{t-1} \mid) + \beta_1 \cdot h_{t-1}$.
APARCH	$x_t = \mu + \sigma \cdot h_t + e_t$, $(h_t)^\delta = \omega + \alpha_1 \cdot (\mid e_{t-1} \mid - \gamma_1 \cdot e_{t-1})^\delta + \beta_1 \cdot (h_{t-1})^\delta$.

Herein, if not stated otherwise, for every statistical test the 5% significance level is assumed.

The Results

Table 1 shows that observations are gathered around mean value. Approximately half of time series are characterized by extremely small positive value and half – by extremely negative one. The largest range is for RTS, and the second largest one is for UX, which can be easily explained by the political situation in these countries. Most of time series are negatively skewed. However, the extreme skewness (*i.e.*, absolute value over 1) is observed only for three time series. For five time series the absolute value of skewness is less than 0.5. For kurtosis (which for the normal distribution is 0) large positive values are observed; the smallest one – for WIG20, and the highest one – for SOFIX. It means that all time series exhibit very strong presence of heavy tails.

Because of extremely low p-values (Table 3) all time series can be assumed as stationary (augmented Dickey-Fuller test) and possessing significant ARCH effects (Lagrange multiplier test). Moreover, none of these time series can be assumed as normally distributed (Jarque-Bera test).

Table 3

P-values of Certain Tests of Time Series

	Jarque-Bera	ADF	ARCH-LM
BET	0.000000	0.000001	0.000000
BUX	0.000000	0.000001	0.000000
PX	0.000000	0.000001	0.000000
SAX	0.000000	0.000001	0.000023
SOFIX	0.000000	0.000001	0.000000
UX	0.000000	0.000001	0.000000
RTS	0.000000	0.000001	0.000000
WIG20	0.000000	0.000001	0.000000

	Jarque-Bera	ADF	ARCH-LM
OMXR	0.000000	0.000001	0.000000
OMXT	0.000000	0.000001	0.000000
OMXV	0.000000	0.000001	0.000000
CROBEX	0.000000	0.000001	0.000000
BIRS	0.000000	0.000001	0.000000
MONEX	0.000000	0.000001	0.000000

All five models (GARCH-M, T-GARCH, GJR-GARCH, E-GARCH and APARCH) were estimated for every time series and their information criteria were computed (Akaike, Shibata, Bayes and Hannan-Quinn). However, due to simplicity only Akaike Information Criterion (AIC) is reported (Table 4).

The first step was to choose for each time series the most suitable model basing on the information criteria (all four criteria gave the consistent results). Unfortunately, in case of five time series (*i.e.*, BUX, UX, OMXR, OMXT and CROBEX) the information criteria prefer models with statistically insignificant coefficients. For BUX the second preferred model is E-GARCH. Fortunately, it has all coefficients statistically significant. (Insignificance of coefficients μ or ω is not problematic, as it means that these coefficients are equal to 0. This does not change the structure of a considered type of a model.) Comparing GARCH-M model, able to describe risk-return trade-off, with asymmetric models, describing the leverage effect, is done in order to choose which of these effects dominate.

On the other hand, for UX and CROBEX there exist no models with all coefficients statistically significant. For OMXR and OMXT the only model with all coefficients statistically significant is GARCH-M. Moreover, this is also the preferred (by AIC) model for OMXV. So now, the whole region can be described by the same kind of a model. Moreover, all rejected models had some problems with autocorrelation and remaining ARCH effects in residuals (not reported herein due to simplicity).

All the models chosen with respect to the above rule, except the one for SAX, present no autocorrelation of squared residuals or the remaining ARCH effects. In order to get rid of ARCH effects in residuals for SAX model (and their autocorrelation); various extensions of the already considered models were evaluated. The success was obtained for GJR-GARCH(2,1).

Table 4

Absolute Values of Akaike Information Criteria and Model Selection

	GARCH-M	T-GARCH	GJR-GARCH	E-GARCH	APARCH
BET	-4.11181	4.12767	4.12103	4.13441	4.12412
BUX	3.93373	3.94539	3.94639	3.94597	3.94376
PX	4.33910	4.35180	4.34676	4.34658	4.34803
SAX	5.15386	5.14704	5.15344	5.15154	5.14965
SOFIX	4.53773	4.53384	4.53517	4.53362	4.53223
UX	3.38364	3.38283	3.38288	3.38441	3.38067
RTS	3.27036	3.27889	3.27654	3.27432	3.27592
WIG20	4.12702	4.13503	4.13070	4.13393	4.13120
OMXR	4.76123	4.76264	4.75942	4.76353	4.75900
OMXT	4.67276	4.67662	4.67305	4.67525	4.67306

	GARCH-M	T-GARCH	GJR-GARCH	E-GARCH	APARCH
OMXV	4.97946	4.97347	4.97501	4.97731	4.97345
CROBEX	4.73027	4.70845	4.73136	4.71459	4.72874
BIRS	5.02418	5.02644	5.02782	5.02825	5.02399
MONEX	4.08474	4.08023	4.08406	4.08416	4.08027

Note: bold – max. absolute value of AIC; shaded – chosen model; For SAX – GJR-GARCH(2,1) was also estimated with absolute value of AIC = 5.1598

It should be reported that GARCH-M model had all coefficients statistically significant for BET, SAX, SOFIX, OMXR, OMXT, OMXV and MONEX. However, for BET the information criteria prefer an asymmetric model, and for SAX the model had remaining ARCH effects in residuals. As a result, for five indices the negative risk-return trade-off is more suitable to describe the behaviour of weekly logarithmic returns than the leverage effect.

The finally chosen, estimated models (Table 4 and Table 1 in the Appendix) happen to have all coefficients statistically significant. Of course, the potential insignificance μ or ω means that these coefficients are equal to 0. However, this is possible and is consistent with the already proved hypothesis of stationarity of analysed time series. It is reminded that GARCH parameters are constrained to be non-negative, while for E-GARCH this is not necessary because the logarithm guarantees positivity of the variance.

Unfortunately, it was impossible to find a model for UX, which would have all coefficients statistically significant. The political situation on Ukraine is the most reasonable explanation, why this index behaves so differently (but such a problem did not occur for Russia). Interestingly, the same problem emerged for CROBEX. In most countries, for which the above methodology lead to asymmetric GARCH model (except just two cases), significant leverage effects were found.

Current findings are in general consisted with the research of Okičić (2014), but there are some important differences. First, for certain countries a different type of a model was found as the suitable one. Secondly, in the current research no significant leverage effect was found for CROBEX and SOFIX. On the other hand, such an effect was found for WIG20, indeed. Still, similarly as Okičić (2014), this research reported the opposite of leverage effect for BIRS, *i.e.,* that positive shocks increase volatility even more than negative shocks. A comparison with her research is also interesting, because, quite similar periods were analysed (*i.e.,* in this research approx. 2 years longer one), but with a different time aggregation.

Results for the Baltic countries are somehow consistent with Aktan *et al.* (2010). Moreover, the current findings do not suffer from insignificance of coefficients. However, herein quite higher variance persistence (Table 7) was found for OMXV than by Teresine (2009). Also, the current research does not prefer asymmetric models for the Baltic countries.

Similarly as Gabriel (2012), here it was found that generalized normal distribution of residuals is more suitable than the normal one. Indeed, also Okičić (2014) rejected the null hypothesis of the normal distribution of residuals, but she conducted no further research in this direction.

All models reported in Table 1 in the Appendix were checked for autocorrelation of squared residuals (Ljung-Box test) and remaining ARCH effects (Lagrange multiplier). Because of high p-values (Table 5) all models passed these diagnostic tests.

Table 5

P-values of Ljung-Box and ARCH-LM Tests

	Q(1)	Q(2)	Q(5)	ARCH-LM(3)	ARCH-LM(5)	ARCH-LM(7)
BET	0.826330	0.878261	0.971133	0.967921	0.972202	0.989430
BUX	0.613044	0.598836	0.840374	0.762528	0.845461	0.917837
PX	0.893766	0.985305	0.984080	0.915414	0.985418	0.995163
SAX	0.659194	0.836266	0.408992	0.333562	0.399891	0.600074
SOFIX	0.765215	0.771420	0.828392	0.915677	0.831057	0.914322
UX	0.923891	0.721653	0.861857	0.741142	0.853191	0.958925
RTS	0.991437	0.848988	0.927557	0.897521	0.934431	0.984329
WIG20	0.293014	0.413442	0.441131	0.546477	0.411101	0.645438
OMXR	0.571990	0.330576	0.355415	0.518955	0.341398	0.440940
OMXT	0.951997	0.675875	0.795587	0.826409	0.809825	0.893394
OMXV	0.951997	0.675875	0.795587	0.922820	0.992974	0.869724
CROBEX	0.791208	0.913715	0.388193	0.202620	0.385949	0.413565
BIRS	0.398014	0.683455	0.401313	0.825976	0.399478	0.405088
MONEX	0.272098	0.546761	0.689281	0.626993	0.715832	0.852043

Unfortunately, the chi-squared test of the goodness of fit for residuals failed in case of SOFIX, OMXR and OMXT (Table 6). Fifty bins were chosen to classify values. Despite several tries to improve the quality of models (Student distribution, generalized hyperbolic one, and their skewed versions) no serious improvements were found. On the other hand, for 11 models out of 14 the chosen specification passed the test, which, in comparison with other researches, seem to be an acceptable result.

Table 6

P-values of Chi-squared Test

	GOF(50)
BET	0.19410
BUX	0.12434
PX	0.92280
SAX	0.08048
SOFIX	0.03474
UX	0.92630
RTS	0.15031
WIG20	0.16687
OMXR	0.00547
OMXT	0.02820
OMXV	0.20390
CROBEX	0.76436
BIRS	0.59518
MONEX	0.92960

It is consistent with already stated result that unconditional variance for UX and RTS is one of the highest amongst the sample (Table 7). However, the two highest numbers characterize CROBEX and MONEX. Also, OMXV has a higher value than UX and RTS. In case of persistence, generally only for SAX it is quite small. Interestingly, persistence for UX and RTS is not very high in comparison to other indices (Table 7). This mean that these markets forget about shocks slightly faster than other CEE ones.

Table 7

Unconditional Variance and Persistence

	unconditional variance	persistence
BET	0.000955	0.986773
BUX	0.001100	0.919391
PX	0.000816	0.899596
SAX	0.000480	0.698068
SOFIX	0.001187	0.983740
UX	0.002033	0.900969
RTS	0.002301	0.933229
WIG20	0.000990	0.959191
OMXR	0.000882	0.985476
OMXT	0.001304	0.991284
OMXV	0.004594	0.999000
CROBEX	0.017513	0.999000
BIRS	0.000299	0.992341
MONEX	0.005399	0.996617

It is also interesting to test the stability of the core parameters. Such a diagnostic was not found in cited researches. On the other hand, it seems reasonable to check whether coefficients do depend on time period. Indeed, there are some evidences for possible time-variability (Jayasuriya & Shambora, 2009).

The critical value of the Nyblom stability test for the given sample is 0.47. As a result, only in case of parameters for PX, WIG20 and CROBEX models the null hypothesis of stability should be rejected (Table 8). The Nyblom (1990) stability test was performed, because the sample consists of observations before and after the recent global financial crisis. There are some evidences that this might be important in case of GARCH-type modelling (Heryan, 2014). By applying this particular test, for example, Charles (2010) and Carstensen (2006) were followed.

Finally, for SAX the Engle-Ng sign bias test indicated some problems. Fortunately, it did not so for any other considered model. However, the model for SAX is the only model out of all investigated, for which certain hard to overcome problems emerged.

Table 8

Statistics of the Nyblom Stability Test

	σ	α_1	α_2	η_1	γ_1	γ_2
BET		0.15920			0.05855	
BUX		0.13154			0.09886	
PX		0.68738		0.06759		
SAX		0.02482	0.05361		0.02448	0.11179
SOFIX	0.10086					
UX		0.06934			0.08770	
RTS		0.30354		0.18084		
WIG20		0.73360		0.60600		
OMXR	0.07568					
OMXT	0.06368					
OMXV	0.06266					
CROBEX		0.86792			0.51002	
BIRS		0.08113			0.05510	
MONEX	0.18160					

Conclusions

In this research, volatility, leverage effects and risk-return trade-off were analysed for Romania, Hungary, the Czech Republic, Slovakia, Bulgaria, Ukraine, Russia, Poland, Latvia, Estonia, Lithuania, Croatia, Serbia, and Montenegro. Weekly returns were analysed. This is a bit unusual choice, because most researches focus on daily data. However, significant effects were found, and, moreover, such a time horizon is used by many investors, indeed. The analysis covered 2005 – 2015 period. GARCH-M and asymmetric T-GARCH, E-GARCH, GJR-GARCH and APARCH models were constructed.

It was found that generalized error distribution is generally the most suitable specification. Significant negative risk-return trade-off was found in four countries (Bulgaria, Latvia, Lithuania and Montenegro). In Estonia significant positive risk-return trade-off was found, which contradicts common expectations. These are relatively small markets. From practical point of view, these findings implicate that, for example, CAPM model is consistent only with Estonian market. Indeed, IMF classifies Estonian economy as an advanced one. On the other hand, negative risk-return trade-off in Bulgaria, Latvia, Lithuania and Montenegro indicate that risky investments are not rewarded by relatively higher returns.

Significant leverage effect was found in five countries: Romania, Hungary, the Czech Republic, Russia and Poland. This outcome is quite consistent with recently studied behavioral aspects of financial markets. Investors are more prone to bad news from the market than to good ones. In case of Russia this might be explained by the additional political risk. The other countries are EU members and their stock markets are quite developed. Oppositely, in Serbia it was found that positive shocks increase volatility more than negative shocks. This might be interpreted that there is much potential for future growths on this market. In other words, investors are expecting rather higher booms than price declines on this market, and market reactions are boosted rather when good news emerge, than if bad ones emerge. In case of Ukraine and Slovakia some weak evidences of leverage effect were found, but these two countries need more investigation. Also, Croatian stock exchange needs more research.

For the Czech Republic and Poland there is significant evidence that leverage effect can vary over time. Current outcomes are partially consistent with certain previous researches. For some – contradictions were found. Therefore, there is still much place for further investigation.

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Appendix

Table 1

Estimated Parameters (Normal Font) and P-values (in Bold)

	μ	ω	α_1	α_2	β_1	η_1	γ_1	γ_2
BET	0.000342	-0.092031	-0.084843		0.986763		0.107659	
	0.251310	0.000000	0.000170		0.000000		0.001239	
BUX	-0.000179	-0.549173	-0.105462		0.919389		0.270356	
	0.894053	0.041379	0.004730		0.000000		0.000248	
PX	0.000940	0.002867	0.167280		0.775314	0.497621		
	0.303281	0.113909	0.038270		0.000000	0.033987		
SAX	0.000503	0.000145	0.028809	0.074485	0.496028		-0.069246	0.266627
	0.000000	0.000000	0.000000	0.012720	0.000000		0.000000	0.000000
SOFIX	0.002389	0.000019	0.119653		0.864051			
	0.000007	0.014753	0.000832		0.000000			
UX	0.001136	-0.613806	-0.032559		0.900969		0.461284	
	0.513186	0.009219	0.440568		0.000000		0.000000	
RTS	0.003866	0.003203	0.108551		0.853856	0.488357		
	0.000016	0.018802	0.000898		0.000000	0.025834		
WIG20	0.000011	0.001284	0.111035		0.873709	0.443134		
	0.992265	0.043094	0.000572		0.000000	0.014897		
OMXR	0.002299	0.000013	0.114797		0.870692			
	0.000004	0.183321	0.000255		0.000000			
OMXT	0.000334	0.000011	0.107959		0.883322			
	0.019907	0.150330	0.000002		0.000000			
OMXV	0.001874	0.000005	0.128295		0.870699			
	0.000000	0.361387	0.000001		0.000000			
CROBEX	-0.000352	0.000018	0.220355		0.744027		0.069235	
	0.645746	0.013618	0.000234		0.000000		0.306268	
BIRS	-0.001434	-0.062171	0.034312		0.992340		0.159284	
	0.009973	0.281773	0.024247		0.000000		0.018123	
MONEX	0.001106	0.000018	0.138110		0.858533			
	0.101001	0.108223	0.008101		0.000000			

Estimated Parameters (Normal Font) and P-values (in Bold)

	σ	shape
BET		1.132884
		0.000000
BUX		1.561663
		0.000000
PX		1.251609
		0.000000
SAX		0.821501
		0.000000
SOFIX	-2.803541	1.070668
	0.003414	0.000000
UX		1.219887
		0.000000
RTS		1.155939
		0.000000
WIG20		1.530996
		0.000000
OMXR	-3.317653	1.092195
	0.000795	0.000000
OMXT	0.845146	1.027986
	0.000507	0.000000
OMXV	-2.129114	0.997141
	0.000007	0.000000
CROBEX		1.357390
		0.000000
BIRS		1.164356
		0.000000
MONEX	-0.738697	1.061522
	0.030906	0.000000