5. Panel GARCH Model with Cross-Sectional Dependence between CEE Emerging Markets in Trading Day Effects Analysis

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Abstract

The presence of the weekday effects of 10 emerging CEE stock markets is explored. Simultaneously, the cross-sectional dependence between daily returns of national stocks is controlled. Most of the previous studies neglect cross-sectional dependence in case of univariate analysis. Rare studies of the weekday effects include multivariate GARCH, considering only a few markets as it suffers from high dimensionality. Thus, we specify and estimate a panel GARCH with a relatively small number of parameters. Results indicate a strong presence of the Monday effect in both mean and variance equations, while the Tuesday effect is present only in the mean equation. Empirical findings also confirm the existence of the cross-sectional dependence, particularly dependence of Poland with Hungary, Czech and Croatia.

Keywords: panel GARCH, time-varying covariance, market anomalies, emerging CEE markets, maximum likelihood estimates
JEL Classification: C32, C33, G1

1. Introduction

It is believed that anomalies in trading with stocks can influence stock market returns as well as volatility. Finding a pattern of these anomalies can be helpful for investors to predict future market movements in speculative purposes, hedging or portfolio management. These anomalies are usually referred to as calendar effects, *i.e.* weekday effects (WDE). According to French (1980), the average return on Monday should be significantly lower than the average return over the other days of the week because of the accumulated information during non-trading days when financial markets are closed. Therefore, accumulated information over the weekend is reflected in prices on Monday. Among others, Fortune

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(1991) explains that firms and governments release good news during the trading time when they can be absorbed and store up bad news after the close on Friday, when investors cannot react until the Monday opening. Another explanation by behavioral finance is that Monday is the worst day of the week for investors because it is the first working day and consequently investors tend to be more pessimistic. On the other hand, investors feel optimistic on Fridays and they are more inclined to sell when prices are rising due to the increased demand.

Empirical results vary regarding different markets and methodology. While the most of empirical findings have focused on developed stock markets as well as emerging markets in Asia and Latin America, only a few studies were concentrating on the Central and Eastern European (CEE) emerging markets. From previous research, there is no general conclusion for WDE in CEE emerging markets. Also, it should be noted that most previous studies focused mainly on OLS regression with dummy variables (Ajayi *et al.*, 2004; Gajdošová *et al.*, 2011; Karanovic and Karanovic, 2018; Tonchev and Kim, 2004) and/or univariate GARCH models, *i.e.* estimation of GARCH model for each market individually (Bubák and Zikes, 2006; Patev *et al.*, 2003; Stavarek and Heryan, 2012; Tonchev and Kim, 2004; Andrieş *et al.*, 2017). These studies neglect cross-sectional dependence in case of univariate analysis, implying unreliable and imprecise conclusions. On the other hand, numerous empirical studies confirmed cross-sectional dependence between CEE countries (Babetskii *et al.*, 2007; Harrison *et al.*, 2010; Ferreira, 2018). Dependence of time series returns across stock markets is opposite to the weak-form efficiency. Weak-form market efficiency means there is no any kind of dependence of time series or anomalies that can explain or predict market movements (Zhang *et al.*, 2017)). Deviations from weak-form market efficiency should not be ignored. Therefore, panel GARCH methodology is used in this paper to explore not only market anomalies, *i.e.* weekday effect, but also the dependence of time series returns across CEE stock markets. Moreover, dependence across markets should be considered due to financial integration and increasing contagion effect indicating that markets move more closely together.

Panel GARCH estimator is extremely valuable for testing panel regressions of financial data for GARCH effects and has a more efficient panel estimator available if the error term is found to be conditionally heteroscedastic.

The main contribution of this paper to the existing literature is employing panel GARCH methodology to investigate WDE. Simultaneously, this methodology upgrades previous studies of WDE by controlling cross-sectional dependence between CEE countries. In the other words, it enables to estimate WDE by assuming already proven "inefficiency" of CEE emerging markets. To the best of the authors' knowledge, none of the previous studies investigated the trading day effects in Central and Eastern European emerging stock markets using panel GARCH.

Second, this methodology enables to find a common day of the week effect in both conditional mean and conditional variance equations for all markets under consideration. However, omitting WDE from both equations can cause spurious conclusion about cross-sectional dependence intensity. Thus, the proposed panel GARCH model gives more accurate cross-market correlations after including WDE.

Third, the existence of cross-sectional dependence, empirically confirmed in this paper, should be considered in all similar studies, which explores any other anomalies in emerging stock markets.

The remainder of the paper is organized as follows. Section 2 presents previous empirical studies. Section 3 describes the data and methodology. Section 4 presents the estimation

results. Finally, some conclusions and directions for future research are provided in Section 5.

2. Previous Empirical Studies

Empirical studies of WDE for CEE emerging markets appeared later than in other countries, after their reforms and stabilization with increased domestic and foreign institutional trading at the beginning of the 21st century. The first serious attempt to investigate WDE in eight CEE emerging stock markets is Patev *et al*. (2003) using univariate GARCH-M model. They have concluded that Monday returns were negative and significant for the Czech and Romanian stock markets. Wednesday returns were significantly positive for the Slovenian market. The WDE was not found in the Polish and Slovak stock markets.

Ajayi *et al*. (2004) have focused on the larger group of 11 emerging stock markets in Central and Eastern Europe (OLS regression was used). Their results indicate negative Monday returns in six markets but only returns in Estonia and Lithuania are significantly negative. According to Tonchev and Kim (2004), various calendar anomalies in the Czech Republic, Slovakia and Slovenia are examined in mean and variance equations. They found only a weak WDE in mean return for Slovenia, but in opposite direction than theory suggests. Bubák and Zikes (2006) have found significant day of the week effects in the mean of returns on the Czech PX and the Polish WIG indices, and significant seasonality in the volatility of the Hungarian BUX index within the framework of a periodic autoregressive model PAR-PGARCH for both the mean and the variance of stock returns. Authors' empirical results indicated the presence of the non-trading effect in the mean of WIG stock returns.

During the crisis period studies of WDE in CEE emerging markets were not in the focus of interest, while after the crisis several studies are provided. The evidence of WDE before and during the financial crisis is compared by Gajdošová *et al*. (2011). Application of regression models with dummy variables leads to the conclusion that WDE was present only in the Czech market (decreasing Monday effect) and the Hungarian market (increasing Friday effect) during the crisis. Results of Guidi *et al*. (2011) also confirm rather sporadic evidence of WDE in CEE stock markets. They have investigated the random walk hypothesis as well as the day-of-the-week effect for CEE stock indices by using parametric and non-parametric tests, as well as OLS and conditional variance methodology. Using the variance ratio test, they found that after the accession to the EU the random walk hypothesis is rejected for two indices, SAX and SOFIX respectively, out of seven. Friday effect features predominantly among indices in the full sample. When the GARCH-M model is employed in the full sample, the day-of-the-week effect is present in both volatility and the returns: particularly Mondays and Tuesdays show a significant effect in the volatility equation of four out of seven indices. Splitting the sample into the pre-accession and post-accession period, results indicate that the volatility Monday effect tends to be present in more indices in the post-accession than in the pre-accession EU period.

Stavarek and Heryan (2012) divided the period 2006-2012 into six sub-periods capturing individual phases of the financial and economic crisis and separately estimated a modified GARCH-M(1,1) model for each country and each sub-period using daily returns of the major national stock market indices. The results clearly indicate a little evidence of the day of the week effect. Daily calendar anomalies are rather sporadic, isolated, and unstable over time. They conclude that the day of the week effect is not typical for the Central European stock markets and the recent financial crisis seems to have no impact on the existence of the WDE phenomenon.

In the recent time, WDE started again to be in the focus of empirical research. Andrieş *et al.* (2017) investigated three seasonal anomalies in return and volatility. Results confirmed the existence of WDE in most countries with exception of (Karanovic and Karanovic, 2018).

The results of recent empirical studies do not provide the general conclusion of WDE in CEE countries. Moreover, all studies in these countries have neglected cross-sectional dependence, which is confirmed in empirical studies (Babetskii *et al.*, 2007; Harrison *et al.*, 2010; Ferreira, 2018). Based on this fact, it is necessary to investigate the existence of WDE in CEE countries in detail. Therefore, our paper uses panel GARCH methodology focused on finding the common WDE in 10 emerging markets that are EU members.

3. Data and Methodology

The dataset of daily prices of the main stock indices provided by Thomson Reuters service, for 10 emerging European markets (Romania - BETI, Hungary - BUX, Croatia - CROBEX, Latvia - OMXRGI, Estonia - OMXTGI, Czech -PX, Slovenia - SBITOP, Bulgaria - SOFIX, Poland – WIG20 and Slovakia - SAX) covers the period from January 4, 2007 to May 13, 2015. These countries are considered because they have not been at the center of the researchers' interest within a recent period after the crisis. A full sample includes 2177 observations for each market. Table 1 presents descriptive statistics of returns according to trading days to get a better insight of weekday effects for all emerging markets together. On average, negative returns are observed on Monday, Tuesday and Thursday, while positive returns are observed on Wednesday and Friday. The highest range of returns can be noticed on Friday but with the smallest standard deviation and positive average return. These findings are informative only but in line with pessimistic Monday and optimistic Friday.

Table 1

Descriptive Statistics of Returns according to Trading Days

	Monday	Tuesday	Wednesday	Thursday	Friday
Mean	-0.0007	-0.0007	0.0002	-7.4e-06	0.0001
Std. Dev	0.0145	0.0136	0.0137	0.0132	0.0135
Minimum	-0.0933	-0.1136	-0.1312	-0.1007	-0.1619
Maximum	0.1478	0.1188	0.1318	0.0915	0.1109

To examine the WDE in returns of emerging markets under consideration, the following panel model is used:

$$r_{it} = \mu_i + Mon \cdot D_1 + Tue \cdot D_2 + Thu \cdot D_3 + Fri \cdot D_4 + \varepsilon_{it}, i = 1,\dots,N, \ t = 1,\dots,T \quad (1)$$

where: N is the number of cross-sectional units (10 national stock indices) and T is the number of time periods (2177 daily observations per unit), r_{it} is return of stock index i in the period t calculated as continuously compounded return or log return, i.e. $r_{it} = \ln p_{it} - \ln p_{it-1}$ with p_{it} being the price of stock index of country i in period t, μ_i is a constant term for each stock market, $D_1 - D_4$ are dummy variables of weekdays and Mon, Tue, Thu, Fri are coefficients to be estimated. The dummy variable for Wednesday is omitted to avoid the dummy variable trap. It seems reasonable to omit the dummy variable for Wednesday as the middle day of the week. The omitted dummy variable becomes the reference category.

Equation (1) is, in fact, the conditional mean equation of returns written in panel data notation. It is necessary to find an adequate estimator for unknowns in the panel model.

The frequently used dynamic panel data estimator difference GMM and system GMM (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998) are proposed for dataset with large N and small T. In case of large T as in this case ($T = 2177$), they can produce inconsistent and potentially very misleading estimates and thus not adequate estimators for an equation (1). On the other hand, there are several estimators for large T. Mean group (MG) estimator and pooled mean group (PMG) estimator (Pesaran, Shin, and Smith, 1999) are suitable for large N and T while Least Squares Dummy Variable (LSDV) estimator is suitable for a large T regardless of the size of N. All these estimators assume that independently distributed error terms across time and cross-sections, *i.e.* they assume cross-sectional independence and constant variance. Finally, seemingly unrelated regression equation (SURE) proposed by Zellner (1962) is suitable for dataset when N is small relative to T and it assumes time-invariant correlation between error terms of different cross-sections. To perform any of the given estimators, several tests must be provided. Some of the considered estimators for a large T, such as LSDV and SURE, assume stationarity. In the first step stationarity of returns is tested, *i.e.* panel unit root tests that have shown good properties when T is large are computed using STATA software: Im, Pesaran and ShinW-stat, ADF-Fisher Chi-square, PP-Fisher Chi-square and Pesaran's CADF[3] test. Results in Table 2 indicate that returns are stationary (the unit root null hypothesis is rejected).

Table 2

Panel Unit Root Tests for Returns

Test	Statistic	p-value
Im, Pesaran and Shin W-stat	-671.34	0.0000
ADF - Fisher Chi-square	2027.90	0.0000
PP - Fisher Chi-square	268.99	0.0000
Pesaran's CADF test t-stat	-15.46	0.0000

Also, it is necessary to test the presence and significance of the individual effects. Wald test is used to test individual effects in equation (1). Wald test statistics is $\chi^2_{(9)} = 1.45$, which is not statistically significant (p-value=0.9975). Therefore, the null hypothesis that all cross-sectional units have a common intercept is not rejected, i.e. all μ_i in equation (1) are equal.

Since all estimators except SURE assume cross-sectional independence, Breusch and Pagan LM test for cross-sectional dependence is computed. This test is appropriate for data sets with fixed N and $T \to \infty$ (De Hoyos and Sarafidis, 2006). The result of LM test indicates cross-sectional dependence according to chi-square value $\chi^2_{(45)} = 10072.38$ (p-value=0.000), which is statistically significant at 1% level. Therefore, it is necessary to use an estimator that enables cross-sectional dependence. Finally, test for the groupwise heteroscedasticity (unconditional) and test of conditional variance are performed. Modified Wald test statistic for groupwise heteroscedasticity in the residuals from a fixed-effect panel model obtains the value $\chi^2_{(10)} = 1116.04$ (p-value=0.000). This test statistic is significant at the 1% level. It indicates that variance is not constant between markets under consideration. Coefficients of

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[3] *Pesaran CADF test (Pesaran, 2007) assumes cross-sectional dependence.*

the partial autocorrelation of squared residuals from a fixed-effect panel model are also calculated as in Cermeño and Grier (2006). Results from Table 3 show that all coefficients of partial autocorrelation up to lag 5 are statistically significant at 1% level. The number of lags included in testing corresponds to the number of trading days in a week. This is the evidence of existing time-varying variance, i.e. conditional heteroscedasticity. Therefore, it is necessary to introduce conditional variance equation that follows the GARCH (1,1) process.

Additionally, Hosking's multivariate Portmanteau autocorrelation test on squared standardized residuals is performed for each time lag (this test is a multivariate extension of the univariate Ljung-Box Q test and requires unstacked data of *N* separated time series) indicating the presence of ARCH effects in residuals for all markets under consideration.

Table 3

Partial Autocorrelation Coefficients of Squared Residuals from Fixed-effect Panel Model and Hosking's Multivariate Portmanteau Test

Lag	PAC	p-value	Q	p-value
1	-0.4647	0.000	2447.32	0.000
2	-0.4719	0.000	4668.53	0.000
3	-0.4677	0.000	6615.85	0.000
4	-0.4611	0.000	8242.38	0.000
5	0.5469	0.000	9531.81	0.000

Considering all pre-estimation results, it can be concluded that the above-mentioned panel data estimators are not suitable for modeling of WDE in emerging markets. The results in Table 3 indicate that ARCH effects are present, so it is necessary to employ the estimator which is a combination of panel data and GARCH methodology. Also, the results of cross-sectional dependence test indicate that range of correlation coefficient across countries is wide (from -0.035 to 0.5710) and thus covariance equation, among mean and variance equations, should be included additionally. Namely, except mean equation, it is necessary to include the equation of variance and the equation of covariance simultaneously in the panel model due to the cross-sectional dependence across markets and time-varying variance. Therefore, the panel GARCH model with cross-sectional dependence includes three equations in the context of panel data. This model was firstly proposed by Cermeño and Grier (2006) and it is adopted here to investigate the presence of the day of the week effects in both mean and variance equations. This methodology is relatively new in financial applications, and it is the only adequate estimation method for this research.

Conditional mean equation (1) can be expressed as a dynamic panel model with fixed effects:

$$r_{it} = \mu_i + Mon \cdot D_1 + Tue \cdot D_2 + Thu \cdot D_3 + Fri \cdot D_4 + \sum_{j=1}^{k} \phi_j r_{i,t-j} + \varepsilon_{it}, i = 1,\ldots,N, \ t = 1,\ldots,T \qquad (2)$$

where: $r_{i,t-j}$ are lagged values of returns and ϕ_j are additional coefficients that should be estimated. In the finance literature, it is known that returns are serially uncorrelated or with minor lower order serial correlation[4], but they are not independent. Significant serial

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[4] *Estimation process was carried out by comparing the results before and after the inclusion of lagged returns up to 5-time lags, but they were not significant. Thus, only one-time lag ($k = 1$)*

correlation of the squared returns and squared residuals respectively indicate the dependence of stock returns in the context of ARCH effects.

Further, the disturbance ε_{it} is assumed to have zero mean and normal distribution with the following conditional moments:

$$
\begin{aligned}
&(i) \ E\left[\varepsilon_{it}\varepsilon_{js}\right] = \sigma_{it}^2, i = j \text{ and } t = s \\
&(ii) \ E\left[\varepsilon_{it}\varepsilon_{js}\right] = \sigma_{ij,t}, i \neq j \text{ and } t = s \\
&(iii) \ E\left[\varepsilon_{it}\varepsilon_{js}\right] = 0, i = j \text{ and } t \neq s \\
&(iv) \ E\left[\varepsilon_{it}\varepsilon_{js}\right] = 0, i \neq j \text{ and } t \neq s
\end{aligned}
\tag{3}
$$

Assumptions (i) and (ii) define a very general conditional variance and covariance process, condition (iii) assumes no autocorrelation and condition (iv) assumes non-contemporaneous cross-sectional correlation. The conditional variance and conditional covariance equations are adopted according to Bollerslev *et al.* (1988) specification of GARCH(1,1) model due to its simplicity and sufficiency to capture the ARCH effects:

$$
\sigma_{it}^2 = \alpha_i + \delta\sigma_{i,t-1}^2 + \gamma\varepsilon_{i,t-1}^2 \qquad i = 1,2,...,N, t = 1,...,T
\tag{4}
$$

$$
\sigma_{ij,t} = \eta_{ij} + \lambda\sigma_{ij,t-1} + \rho\varepsilon_{i,t-1}\varepsilon_{j,t-1} \qquad i \neq j
\tag{5}
$$

The model defined by equations (2), (4) and (5) is a dynamic panel data model with conditional covariance (DPD-CCV). It is convenient that both equations (4) and (5) follow a common dynamic according to GARCH (1,1) specification, *i.e.* it captures the dynamic properties of disturbances ε_{it} and their cross-products $\varepsilon_{it} \cdot \varepsilon_{jt}$. In this way, the number of parameters is considerably reduced (there are $4 + N(N+1)/2$ parameters in the covariance matrix). Given the "excessive" number of parameters estimated in DPD-CCV model, it still includes fewer parameters compared to some MGARCH type specifications[5]. Furthermore, the conditional variance equation (4) assumes $\alpha_i > 0$, $\delta \geq 0$, $\gamma \geq 0$ and $(\delta + \gamma) < 1$ as sufficient restrictions to ensure the positivity and convergence of σ_{it}^2. Equation (5) is conditional covariance equation, assuming $(\lambda + \rho) < 1$ to ensure the covariance processes to converge to some fixed value. A different individual effect for each market in conditional variance equation is supported from the modified Wald test for heteroscedasticity. Some authors have also tested the day of the week effect in volatility using univariate approach (Choudhry, 2000; Berument and Kiymaz, 2001; Tonchev and Kim, 2004; Bubák and Zikes, 2006). Therefore, conditional variance equation (4) is extended in the following way:

$$
\sigma_{it}^2 = \alpha_i + Mon_\sigma \cdot D_1 + Tue_\sigma \cdot D_2 + Thu_\sigma \cdot D_3 + Fri_\sigma \cdot D_4 + \delta\sigma_{i,t-1}^2 + \gamma\varepsilon_{i,t-1}^2, \quad i =,1...,N, \ t = 1,...,T
\tag{6}
$$

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was considered due to robustness check of the weekday effects in mean, assuming that AR parameter satisfies the stability condition.

[5] *For example DVEC(1,1) model, proposed by Bollerslev* et al. *(1988), would include 165 parameters, while it's vector-diagonal version proposed by Bollerslev* et al. *(1994), would include 75 parameters. Due to dimensionality problem, many of the estimated parameters would not be statistically significant, while additional computational problems arise in the numerical optimization procedure.*

Equation (6) follows the similar specification of the day of the week effect as in equation (2) and it is considered in this paper.

In matrix notation equation (2) with AR(1) parameter can be written as:

$$r_t = \mu + Z_t\theta + \varepsilon_t, \qquad t = 1,...,T \tag{7}$$

where: r_t and ε_t are vectors of dimension $N \times 1$, matrix $Z_t = [r_{t-1}, D_1, D_2, D_3, D_4]$ has dimension $N \times 5$, μ is a $N \times 1$ vector of individual specific effect, while $\theta = [\varphi_1, Mon, Tue, Thu, Fri]'$ is a column vector of unknown coefficients. Considering previous assumptions, the N-dimensional vector of disturbances $\varepsilon_t \sim N(0, \Omega_t)$. The covariance matrix Ω_t is time-dependent; its diagonal and off-diagonal elements are given by equations (4) and (5) or (6) respectively. The vector of returns r_t is therefore conditionally normally distributed with mean $(\mu + Z_t\theta)$ and variance-covariance matrix Ω_t with its conditional density:

$$f(r_t | Z_t, \mu, \theta, \phi) = (2\pi)^{-\frac{N}{2}} |\Omega_t|^{-\frac{1}{2}} e^{-\frac{1}{2}(r_t - \mu - Z_t\theta)' \Omega_t^{-1}(r_t - \mu - Z_t\theta)} \tag{8}$$

where: φ includes the parameters in equations (4) and (5) or (6) respectively. The log-likelihood function of the complete panel GARCH can be written as:

$$l = -\frac{NT}{2}\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\ln|\Omega_t| - \frac{1}{2}\sum_{t=1}^{T}(r_t - \mu - Z_t\theta)'\Omega_t^{-1}(r_t - \mu - Z_t\theta) \tag{9}$$

Equation (9) is maximized with respect to μ, θ and φ using the numerical optimization algorithm BFGS. It is well known that under regularity conditions the MLE estimators are consistent, asymptotically efficient and asymptotically normally distributed with mean equal to the true parameter vector and a covariance matrix equal to the inverse of the corresponding information matrix. It is important to note that these asymptotic properties would hold for N fixed and T approaching infinity since we are modeling the N-dimensional vector of disturbances of the panel as a multivariate time series process.

4. Estimation Results

To examine the day of the week effects in both mean and variance equations using daily returns of 10 national stock indices from CEE emerging markets, four panel GARCH models are estimated in the first step, while in the second step two additional panel GARCH are estimated for robustness check. In theory, it is expected that returns are serially uncorrelated but in practice, many researchers found positive and statistically significant autocorrelation of returns for some countries. Therefore, the basic model, labeled as Model 1, is specified without the lagged dependent variable. To examine the possibility that returns follow autoregression process of the first order lagged dependent variable is introduced in Model 2 and Model 4. Moreover, some empirical researches have provided evidence that WDE has the influence on a variance of returns thus dummy variables of weekdays are also included in two specifications (Model 3 and Model 4). All results are obtained using RATS software using MLE within BFGS algorithm (Table 4).

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Table 4

Estimation Results of Different Panel GARCH Specifications using MLE

Parameter	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
φ_1		0.0132		0.0132		
		(0.0092)		(0.0088)		
μ	0.0003**	0.0003	0.0002	0.0003	0.0001	0.0004**
	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Mon	-0.0012**	-0.0012***	-0.0012***	-0.0013***	-0.0006**	-0.0014***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0001)
Tue	-0.0005**	-0.0005	-0.0006***	-0.0005**	-0.0004*	-0.0009***
	(0.0002)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0001)
Thu	-0.0002	-0.0002	-0.0002	-0.0002	-0.0001	-0.0005***
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0001)
Fri	0.0002	0.0002	0.0002	0.0002	0.0002	0.0001
	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0001)
δ	0.8830***	0.8829***	0.8830***	0.8830***	0.8555***	0.8789***
	(0.0067)	(0.0068)	(0.0065)	(0.0066)	(0.0049)	(0.0077)
λ	0.9175***	0.9176***	0.9174***	0.9176***	0.8976***	0.9145***
	(0.0067)	(0.0070)	(0.0071)	(0.0068)	(0.0071)	(0.0077)
γ	0.0809***	0.0809***	0.0809***	0.0809***	0.0872***	0.0820***
	(0.0043)	(0.0046)	(0.0043)	(0.0042)	(0.0062)	(0.0049)
ρ	0.0297***	0.0296***	0.0297***	0.0296***	0.0356***	0.0304***
	(0.0024)	(0.0025)	(0.0023)	(0.0024)	(0.0025)	(0.0027)
Mon_σ			-0.0012***	-0.0012***	-0.0002	-0.0014***
			(0.0004)	(0.0004)	(0.0005)	(0.0003)
Tue_σ			-0.0006	-0.0005	-0.0004	-0.0009***
			(0.0004)	(0.0003)	(0.0004)	(0.0003)
Thu_σ			-0.0002	-0.0002	-0.0001	-0.0005
			(0.0004)	(0.0004)	(0.0005)	(0.0003)
Fri_σ			0.0002	0.0002	0.0001	0.000007
			(0.0004)	(0.0004)	(0.0005)	(0.0003)

Note: *, **, *** represent significance at the 1%, 5% and 10% level, while standard errors are in parentheses.

In both models with lagged dependent variable, Model 2 and Model 4, respectively, the AR parameter is not statistically significant even positive. This finding confirms theoretical assumption about serially uncorrelated returns. Moreover, the introduction of lagged dependent variable didn't change other parameter estimates. Comparing the first and the second model, statistically significant common parameters are $Mon, \delta, \lambda, \gamma$ and ρ, while in Model 1 μ and *Tue* are additionally statistically significant. Model 3 and Model 4 are augmented by including the day of the week effect in conditional variance equation. Results of both models are almost identical. Statistically significant parameters are $Mon, Tue, \delta, \lambda, \gamma, \rho$ and Mon_σ, while φ_1 is not significant in Model 4. From all results, it can be concluded that Model 3 is the most appropriate thus results from this model are considered in economic interpretation. Moreover, the results from Model 1, 2 and 4 are almost equal as in the Model 3.

To additionally ensure the robustness of the results, the entire sample was split into two subsamples. The first subsample of 800 observations covers pre-crisis period while the second subsample includes 1400 observations. Therefore, two additional models were estimated, *i.e.* Model 5 and Model 6, with results in the last two columns of Table 4. Robustness is confirmed in the context of parameter estimates but minor differences in statistical significance can be noticed. Namely, Monday and Tuesday effects in mean are statistically significant in both subsamples but Thursday effect is significant in crisis and post-crisis period only, with the expected negative sign. Even though the Friday effect is found to be positive, supported by a theoretical explanation, it is not statistically significant in both equations and both subsamples. In the variance equation, Monday and Tuesday effects are significant only in the second subsample period. In the recent paper of Andrieş *et al.*, (2017), authors found significant Monday effect in the more than half of the examined countries. Therefore, the significance of the Monday effect in our research is expected. However, results of the Tuesday effect are in the line with research of Karanović and Karanović (2018).

It should be noted that parameters δ, λ, γ and ρ, are statistically significant in all estimated models and their values are very similar. In particular, the GARCH (1,1) model usually indicates high persistence in the conditional variance when $\delta + \gamma = 1$, *i.e.* almost integrated behavior of the conditional variance. High volatility persistence means that a long time is needed for shocks in volatility to die out. Based on estimated results from Model 3, as most appropriate, the sum σ+γ=0.9639 indicates high volatility persistence at observed emerging markets. In other words, the conditional variance converges to unconditional long-run variance very slowly (3.61% daily). We find that all individual specific effects in the variance equation are statistically significant at the 1% level (see Appendix A). It is expected that different levels of unconditional variance within each market can be computed due to different constant terms α_i and hence it can be easily noted that unconditional variance depends straightforward on individual specific effects. Therefore, our results suggest that Hungary, Romania, Poland Slovakia and the Czech Republic are expected to be riskier in the future, as they have a high level of unconditional volatility, while Estonia, Latvia, Slovenia, Croatia, and Bulgaria have a low level of unconditional volatility (see Appendix B).

From the constant terms η_{ij}, $i \neq j$ in covariance equation (5), implied conditional cross-sectional dependence in pairs of markets can be computed. As the results for the covariance equation also indicate a quite persistent although stationary GARCH (1,1) process (σ+λ=0.9471), the unconditional covariance can be computed as $\eta_{ij} / (\lambda + \rho)$. Moreover, from unconditional covariance and unconditional variance, the long-run cross-correlation coefficient in pairs can be obtained. Long-run cross-correlation coefficients matrix is presented in Appendix C. Results indicate that in the long-run high positive cross-correlation is expected between Poland and the Czech Republic, Poland and Hungary and Poland and Croatia. These results are expected, *i.e.* Harrison *et al*. (2010) confirmed that the Czech Republic, Hungary and Poland display higher correlations among them and with the other EU markets. Additionally, Šikić and Šagovac, (2017), confirm that the Croatian stock market is more correlated with the Polish stock market than the US. These results confirm the dominance of Poland stock market in the CEE region. The cross-correlation is negative but close to zero, between Slovakia and most other countries. These results are in the line with Babetskii *et al*. (2007). They found that Slovak returns are not correlated with the Czech Republic, Hungary and Poland. They d   escribed the Slovak stock market as moderate development and lower than others. Therefore, it can be concluded that during the ten years Slovak stock market stays isolated from other new EU countries.

5. Conclusion

In this paper, we employ the panel GARCH model with cross-sectional dependence to investigate the presence of the WDE in daily returns on 10 European emerging markets in both conditional mean and conditional variance equations. Most of the previous empirical studies neglect possible cross-country dependence using the univariate approach which reports only country-by-country results. Empirical evidence of time-varying conditional variance and covariance of these markets imposed the need to include cross-sectional dependence in a panel model. This finding makes panel GARCH methodology unique and appropriate one. Therefore, the main contribution of this paper is the extension of traditional GARCH model to a panel context, *i.e.* novel methodology enables to explore not only market a   nomalies but also the dependence of time series returns across CEE stock markets.

The empirical findings indicate the strong presence of the common Monday effects in both mean and variance equations, while the Tuesday effect is significant only in the mean equation. High volatility persistence at observed emerging markets is present. Our results implicate that Hungary, Romania, Poland Slovakia and the Czech Republic are expected to be riskier in the future, while Estonia, Latvia, Slovenia, Croatia and Bulgaria have the low level of unconditional volatility. In the long-run high positive cross-correlation is expected between Poland and the Czech Republic, Poland and Hungary, Poland and Croatia. The cross-correlation is negative but close to zero, between Slovakia and most of the other countries. Trading anomalies findings on Mondays and Tuesdays can be helpful to investors to predict future market movements in speculative purposes, hedging or portfolio adjustment. Moreover, information about cross-markets dependence is extremely valuable for international portfolio diversification. Recommendation for risk-averse international investors is to invest in stocks of Estonia, Latvia, Slovenia, Croatia and Bulgaria. Moreover, investors who are interested in emerging markets should include Poland stocks in their international portfolios for diversification purpose, even   though it has a relatively high risk position among neighboring countries.

As the purpose was to find common trading anomalies across emerging markets, i.e. weekday effects, developed ones are not included in the analysis. This is a limitation of the research. It would be interesting to include not only other European markets but also US markets, as we can assume that emerging markets depend on developed markets. In that case, a panel GARCH model should be adapted to control local and global cross-sectional dependence. Moreover, high-frequency data (thick-by-thick) should be explored to check the number of transactions   and trading volumes on Mondays, Tuesdays, Wednesdays, Thursdays and Fridays for emerging markets under consideration. Such data can be used to identify significant jumps within trading days of the week. Finally, our results can motivate researchers to deeply investigate cross-sectional dependence between emerging markets in the other economics behaviors and motivate them to perform panel GARCH in their studies.

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Appendix

A. Matrix of Estimated Individual Specific Effects in Conditional Variance and Conditional Covariance

Model 3	Romania	Hungary	Croatia	Latvia	Estonia	Czech	Slovenia	Bulgaria	Poland	Slovakia
Romania	0,0000081814***									
Hungary	0,0000032918***	0,0000099251***								
Croatia	0,0000020338***	0,0000017669***	0,0000037644***							
Latvia	0,0000012619***	0,0000005662	0,0000008293***	0,0000048331***						
Estonia	0,0000022478***	0,0000018897***	0,0000012454***	0,0000013044***	0,0000052991***					
Czech	0,0000033630***	0,0000047664***	0,0000018174***	0,0000009163***	0,0000021742***	0,0000066075***				
Slovenia	0,0000012477***	0,0000006189*	0,0000007729***	0,0000005223*	0,0000007937***	0,0000008375***	0,0000038844***			
Bulgaria	0,0000012207***	0,0000007952**	0,0000009261***	0,0000005894**	0,0000011156***	0,0000011777***	0,0000006624**	0,000003741***		
Poland	0,0000033473***	0,0000056527***	0,0000020026***	0,0000004691	0,0000016153***	0,0000047044***	0,0000006686**	0,000001076***	0,0000079879***	
Slovakia	-0,000000342	0,000000110	-0,000000121	-0,000000252	-0,000000050	-0,0000001361	-0,0000000024	0,000000106	-0,0000002778	0,0000072481***

Note: *, **, *** represent significance at the 1%, 5% and 10% level.

B. Matrix of Unconditional Variance and Covariance

Model 3	Romania	Hungary	Croatia	Latvia	Estonia	Czech	Slovenia	Bulgaria	Poland	Slovakia
Romania	0,000008488									
Hungary	0,000003476	0,000010297								
Croatia	0,000002147	0,000001866	0,000003905							
Latvia	0,000001332	0,000000598	0,000000876	0,000005014						
Estonia	0,000002373	0,000001995	0,000001315	0,000001377	0,000005498					
Czech	0,000003551	0,000005033	0,000001919	0,000000967	0,000002296	0,000006855				
Slovenia	0,000001317	0,000000654	0,000000816	0,000000551	0,000000838	0,000000884	0,000004030			
Bulgaria	0,000001289	0,000000840	0,000000978	0,000000622	0,000001178	0,000001243	0,000000699	0,000003880		
Poland	0,000003534	0,000005968	0,000002114	0,000000495	0,000001705	0,000004967	0,000000706	0,000001136	0,000008287	
Slovakia	-0,000000362	0,000000117	-0,000000128	-0,000000266	-0,000000053	-0,000000144	-0,000000003	0,000000112	-0,000000293	0,000007520

C. Matrix of Long-run Cross-correlation Coefficients

Model 3	Romania	Hungary	Croatia	Latvia	Estonia	Czech	Slovenia	Bulgaria	Poland	Slovakia
Romania	1,000000									
Hungary	0,409489	1,000000								
Croatia	0,252998	0,181181	1,000000							
Latvia	0,156976	0,058059	0,224208	1,000000						
Estonia	0,279619	0,193773	0,336705	0,274676	1,000000					
Czech	0,418346	0,488756	0,491350	0,192951	0,417574	1,000000				
Slovenia	0,155210	0,063470	0,208960	0,109984	0,152437	0,128998	1,000000			
Bulgaria	0,151851	0,081541	0,250379	0,124114	0,214261	0,181398	0,173553	1,000000		
Poland	0,416393	0,579638	0,541420	0,098782	0,310175	0,724608	0,175178	0,292749	1,000000	
Slovakia	-0,042593	0,011321	-0,032686	-0,053086	-0,009584	-0,020963	-0,000629	0,028872	-0,035394	1,000000