4. DO SEASONAL ANOMALIES STILL EXIST IN CENTRAL AND EASTERN EUROPEAN COUNTRIES? A CONDITIONAL VARIANCE APPROACH

Alin Marius ANDRIEŞ[1], Iulian IHNATOV[2], Nicu SPRINCEAN[3]

Abstract

Given the Efficient Market Hypothesis (EMH), the aim of this paper is to investigate three seasonal anomalies, both in return and volatility – that is, the day-of-the-week effect, the week-of-the-month effect, and the month-of-the effect, respectively, for a sample of 11 countries from Central and Eastern Europe area from 2000 to 2015 by employing a conditional variance approach. Our results show that the EMH does not hold for all the markets we have surveyed. Moreover, the seasonal effects are also present in the volatility equations. Therefore, these markets are not efficient, giving rise to arbitrage opportunities. Hence, the investors may take advantage of these anomalies by designing profitable trading strategies which account for transaction costs and make abnormal returns.

Keywords: seasonal anomalies, efficient market hypothesis, arbitrage, stock market
JEL Classification: G11; G14

1. Introduction

The Efficient Market Hypothesis (EMH) is nowadays one of the leading concepts in the world of finance, being developed by Fama (1965, 1970) who is now credited as the father of the hypothesis. It broadly states that security prices follow a random walk, reflecting all public available information: if new information becomes available about a stock, an industry or the economy, an efficient market will integrate that information very quickly. If, however, the information is not fully integrated in the security prices, then the market is less than fully efficient[4]. Markets that are less than fully efficient give rise to arbitrage opportunities

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[1] Alexandru Ioan Cuza University of Iasi, Faculty of Economics and Business Administration, 22 Carol I Boulevard, Iasi 700505, Romania. E-mail: alin.andries@uaic.ro.

[2] Alexandru Ioan Cuza University of Iasi, Faculty of Economics and Business Administration, 22 Carol I Boulevard, Iasi 700505, Romania. E-mail: iulian.ihnatov@uaic.ro.

[3] Corresponding author, Alexandru Ioan Cuza University of Iasi, Faculty of Economics and Business Administration, 22 Carol I Boulevard, Iasi 700505, Romania. E-mail: sprincean.nicu@uaic.ro.

[4] Fama (1970) distinguishes three types of market efficiency: (1) weak form, which includes all historical security price information to current security prices; (2) semi-strong form of

(abnormal returns) because the inefficiency causes a security mispricing - a deviation from the predictions of the EMH. If the mispricing is well-known and persistent, then it is referred to as an anomaly (Singal, 2004).

The rationale of this paper has two roots. First, from an investor's perspective (both long-term and speculative): to be readily exploitable, an anomaly must be persistent or be predictable. Hence, what are the main causes behind the well-known anomalies and what are the best lucrative trading strategies to implement and take advantage of these anomalies? Second, from a researcher's perspective: seasonal anomalies have been extensively studied for the developed countries (with a high degree of liquidity) given their long track records of public market data and a robust dataset, but far less for the transition or emerging markets (which are less liquid). The Central and Eastern European (CEE) countries have been in the last decade in the sight of both individual and institutional investors due to their strong economic growth perspectives and attractive returns on investment, driven especially (for some of them) by the integration into the European Union, which led to the development of corporate governance principles, liberalization of the economy and a stronger system of property rights, one of the most fundamental requirements of a capitalist economy (Altar et al., 2015; Miletić and Miletić, 2016). Thereby, a near-exhaustive study for Central and Eastern European countries will definitely enrich the academic knowledge regarding this topic.

The seasonal (or calendar) anomalies are cyclical anomalies in return, where the cycle is based on the calendar. Besides the security price, an anomaly affects also the volatility, volume and bid-ask spread. The most studied and widely accepted calendar anomalies are the weekend effect and the January effect. The weekend effect, first discovered in the 1970s, refers to the phenomenon in which the average returns on Mondays are significantly lower than those occurring on preceding Fridays. There are some explanations behind this anomaly. Slager (2006) identifies three key determinants of the weekend effect: *(1) information theory* – the amount of the news released at the end of the week is higher than for any other day of the week. Moreover, the news reports on Monday are more likely to carry bad news than good news thus affecting the security prices; *(2) short-selling* – liquidation of the positions before the weekend (creating a higher buy volume) and reopening the short-selling exposure on Monday (creating a higher short volume), and *(3) investor behavior* – the weekend enables the investors to reanalyze their exposure and rebalance their portfolios, based on the information collected during the weekend, usually on Monday. A simple investment strategy to implement here to exploit this anomaly is to buy the stocks on Monday and sell them on Friday.

The January effect is a general and appreciable increase in security prices in January. The primary explanation of this anomaly is the tax-loss selling hypothesis: the investors sell their price-declining shares (losers) at the end of the fiscal year (December) in order to realize capital losses to offset capital gains and hence reduce their tax liability (and maximize the actual value of the tax shield) and further repurchase them in January, as suggested by Thaler (1987). Further, the rational investors should sell their price-increasing shares (winners) in January instead of December, deferring the tax payment by one year. Also,

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efficiency, considering that all public available information (earnings announcements, stock splits etc.) is reflected into security prices and (3) strong form in which both public and private information is reflected into security prices. However, in recent years, financial literature adopted another classification, the market being considered less or more efficient (see Lim and Brooks, 2011).

another possible determinant of the January effect could be the transaction costs (brokerage fees and bid-ask spread) that detain the arbitrage opportunities in certain periods of the year. According to Bhardwaj and Brooks (1992) transaction costs are not stable, reaching higher values near the turn of the year.However Keim (1983), Reinganum (1983) and Singal (2004) point out that the January effect is mainly due to the small-cap stocks and once the small stocks are removed, the January effect disappears. To gain abnormal returns, investors should buy loser stocks in December and sell them in January.

Another seasonal anomaly to be considered is the first-week-of-the-month effect (the week-of–the-month effect). Although this effect is not widely studied in the academia, following Kohli and Kohers (1992) our intention is to test whether the average returns in the first week of each month are statistically higher than the average returns in any other weeks of the month. If this anomaly is valid, investors should take advantage by going long in the remaining weeks of the month and short in the first week.

Even though these anomalies are often interpreted as a violation of the EMH, they may have other non-economic causes as well, such as data mining, survivorship bias, small sample bias, selection bias or non-synchronous trading. Singal (2004) discusses these causes in detail.

The rest of the paper is organized as follows. The next chapter will review the theory on financial market anomalies. Section 3 will present the data and methodology, while the last two sections will present the results and will draw the conclusions of this research.

2. Literature Review

The day-of-the-week (DOW) and the month-of-the-year (MOY) effects have extensively been studied by various authors, suggesting contradictory results for different areas or periods, but also confirming or refuting these anomalies, and thus, the EMH. This is especially due to the specific characteristics of each particular market, including size, liquidity and maturity of the capital market, the business cycle, the organizational structure, the degree of integration and liberalization etc.

Oprea and Ţilică (2014) reveal the presence of the Friday effect on the Romanian stock market between 2005 and 2011. These findings contradict those of Diaconaşu *et al*. (2012) who investigate the presence of the-day-of-the week and the-month-of-the-year effects in the Romanian equity market between 2000 and 2011. Their results show the presence of the Thursday effect and lower mean returns on Fridays in the case of BET-C index in the pre-crisis period. Also, the results of Kanaryan *et al*. (2002) document that the Czech and Romanian markets have significant negative average returns on Mondays and the Slovenian market has significant positive average returns on Wednesdays. Singh (2014) examines the existence of the DOW and MOY effects in BRIC countries across 10 years (2003-2013) and concludes that they occur only in China. The conclusions, however, are in contradiction with those of Gahlot and Datta (2012) and Parikh (2009), who evidence the Indian stock market inefficiency.

Asteriou and Kavetsos (2006) test the presence of the January and MOY effects for eight transition countries from 1991 until 2003. Their research shows strong evidence in favor of the January effect in four of the sampled countries (Hungary, Poland, Romania, and Slovakia) and of the tax-loss selling hypothesis for two country cases (Hungary and Romania). Their results are inconsistent with other similar studies (*e.g.*, Heininen and Puttonen, 2008, Georgantopoulo *et al*., 2011, Guidi *et al*., 2010 and Dragota and Oprea, 2014).

Kiymaz and Berument (2003) carried out an analysis of the DOW effect in a conditional variance framework for five developed countries (Canada, Germany, Japan, the United Kingdom, and the United States) between 1988 and 2002. Their results indicate that the DOW effect is present in both return and volatility equations for every market they investigate. Also, Moller and Zilca (2008) findings provide evidence for higher abnormal returns in the first part of January and lower abnormal returns in the second part of January in the 1995-2004 period. Furthermore, Dzhabarov and Ziemba (2010) show that small-caps underperformed large-caps in January in only five years out of 70 (1926-1995). The authors conclude that, in comparison with other anomalies, the monthly effect does not appear to be useful to traders and investors probably because of transaction costs.

French (1980), one of the pioneers in this field, examines the process generating stock returns by comparing the returns for different days of the week. The author computes the daily returns for Standard and Poor's composite portfolio for a period of 25 years (1953-1977). His empirical findings indicate that the mean return for Monday was significantly negative each of the five five-year sub-periods, as well as over the full period, being inconsistent with both calendar and trading time models while the average return for the other four days of the week was positive.

Rozeff and Kinney (1976) first documented the January effect and found seasonal patterns in an equal-weighted index of NYSE prices over the 1904-1974 period and found out that one-third of the annual returns occurred in January alone. Also, in line with these results, Gultekin and Gultekin (1983) found a seasonal pattern in the stock returns in the most of analyzed countries, *i.e.* large returns occurring in January as compared to the other eleven months, related to the turn of the tax year (tax-loss selling hypothesis). However, seasonality in these countries there is not a size related anomaly, as the authors suggest. Keim (1983) reports that nearly 50% of the average magnitude of the risk-adjusted premium of small firms observed by Banz (1981) and Reinganum (1981), relative to large firms for the period under investigation is due to anomalous January abnormal returns.

The week-of-the-year (WOY) effect is not as widely addressed as other similar seasonal anomalies. It shows that there are different weekly return patterns for different weeks of the month. Levy and Yagil (2012) study the WOY effect in twenty countries around the world using 34,945 observations of weekly data. The authors found that the WOY effect persists in 19 countries out of 20. Kohli and Kohers (1992), using weekly data for the S&P 500 Composite Index, show that the weekly returns are significantly positive during the first week of a month only. For the remaining weeks of a month, the findings seem to be statistically indistinguishable from zero.

3. Data and Methodology

The data used in our econometric analysis consist of the daily, weekly and monthly observations of the stock market benchmark indexes of eleven countries from the Central and Eastern European area, expressed in each countries' national currency, namely: BET for Romania, BUX for Hungary, MICEX for Russia, OMXR for Latvia, OMXT for Estonia, OMXV for Lithuania, PX for Czech Republic, SAX for Slovakia, WIG for Poland, SBI TOP for Slovenia, and SOFIX for Bulgaria. We have collected daily data from the Datastream database that spans from 01/03/2000 to 12/31/2015 for the above-mentioned first nine countries, from 3/31/2006 to 12/31/2015 for Slovenia and from 10/20/2000 to 12/31/2015 for Bulgaria. We have chosen these periods of time as they encompass a lot of events that may have been affected the data.

Daily, weekly and monthly returns (R_t) are computed in continuous time as the first difference in the natural logarithms of the stock market indexes:

$$R_t = \ln\frac{P_t}{P_{t-1}} \tag{1}$$

where: P_t and P_{t-1} are the price index at time *t* and *t-1*, respectively.

Usually, the price time-series data is non-stationary. The Augmented Dickey-Fuller reveals that the data are integrated of the first order (I(1)). Computing the returns, we remove the non-stationarity.

In our work, we test for seasonal effects and specific effects (the weekend effect, the first-week-of-the-month effect and the January effect) employing GARCH models. We do not use the standard OLS approach as it has two drawbacks. On one hand, autocorrelation causes misleading inferences, while we may just correct the standard errors to obtain robust *t-statistics* by using Newey-West estimators. On the other hand, error variances may not be constant and, as in the case of autocorrelation, White correction does not cut them out. These reasons, along with others, explained below, compelled us to address these shortcomings through GARCH models. Volatility has been an underlying variable in modeling financial time series, designing trading strategies and implementing risk management. Higher volatility means higher uncertainty, which may bring huge losses to investors and make a difficult task for companies to raise capital in the capital markets. We often notice that volatility tends to cluster together, suggesting that volatility is autocorrelated and changing over time. The main advantage of employing GARCH models in our study is the ability to capture the common empirical observations usually in daily time series: fat tails due to time-varying volatility, skewness resulting from mean non-stationarity, non-linearity dependence, and volatility as pointed out by Pagan (1996).

The conditional variance equation for the standard GARCH (1, 1) can be specified as follows:

$$h_t = \gamma_0 + \gamma_1\varepsilon^2_{t-1} + \gamma_2 h_{t-1} \tag{2}$$

with $\gamma_0 > 0$, $\gamma_1 \geq 0$, $\gamma_2 \geq 0$ for the non-negativity of the conditional variance and $\gamma_1 + \gamma_2 < 1$ to satisfy the non-explosiveness of the conditional variances. Coefficient γ_1 shows the impact of current news on the conditional variance process while the coefficient γ_2 shows the persistence of volatility after a shock, or the impact of old news on volatility. Furthermore, the persistence of shocks to volatility depends on the $\gamma_1 + \gamma_2$ sum. Engle and Bollerslev (1986) point out that for $\gamma_1 + \gamma_2 < 1$ values volatility tends to decrease over time, at a slower rate as the sum is closer to unity, whilst for values $\gamma_1 + \gamma_2 \geq 1$ volatility persists over time.

Following Kiymaz and Berument (2003) we model the conditional variability of stock returns, including the day-of-the-week, the week-of-the-month and the month-of-the year effects into volatility equation thus allowing the constant term of the conditional variance equation to vary for each day, week and month. Therefore, our variance equations, corresponding to the three seasonal effects we investigate, will take on the following forms:

$$h_t = \gamma_0 + \gamma_1\varepsilon^2_{t-1} + \gamma_2 h_{t-1} + \sum_{i=2}^{5}\beta_i D_{it} \tag{2.1}$$

$$h_t = \gamma_0' + \gamma_1'\varepsilon^2_{t-1} + \gamma_2' h_{t-1} + \sum_{i=2}^{5}\beta_i D'_{it} \tag{2.2}$$

$$h_t = \gamma_0'' + \gamma_1''\varepsilon^2_{t-1} + \gamma_2'' h_{t-1} + \sum_{i=2}^{12}\beta_i D''_{it} \tag{2.3}$$

where: D_{it}, D'_{it} and D''_{it} are the dummy variables such that $D_{it} = 1$ if day *t* is a Monday and zero otherwise, $D'_{it} = 1$ if week *t* is week 1 and zero otherwise, $D''_{it} = 1$ if month *t* is January and zero otherwise, and so forth.

As pointed out by Brooks (2008), the standard GARCH (p, q) model may not be appropriate in time-series data, since (1) the non-negativity conditions may be violated by the estimated model, (2) GARCH model cannot account for leverage effects (a drop in the stock price for a particular company makes the company's D/E ratio rise), (3) it does not allow for any direct feedback between conditional variance and the conditional mean and in particular for modeling the behavior of stock returns (equity markets), (4) it imposes a symmetric response of volatility to positive and negative shocks (*i.e.* what matters is the absolute value of the innovation, not its sign, as the residual term is squared). However, a negative shock (bad news) is likely to cause the volatility to increase more than a positive shock (good news) of the same intensity. This could be better exemplified by looking at the volatility during the financial crisis started in 2008: implied volatility reacted asymmetrically to up and down stock market moves. To avoid these shortcomings, a series of modification to the original GARCH model have been added. One of them is the exponential GARCH (or EGARCH) firstly proposed by Nelson (1991). The variance equation for an EGARCH (1, 1) model is given by:

$$\log(h_t) = \gamma_0 + \gamma_1\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma_2\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma_3\log(h_{t-1}) \quad (3)$$

where: γ_0, γ_1, γ_2, γ_3 and α_i being the parameters to be estimated.

The EGARCH model has basically two key advantages if compared with the standard GARCH. First, the inclusion of the log function makes the conditional variance positive and thus the non-negative constraint on parameters used in the GARCH model is not necessary anymore. Second, asymmetries are allowed under the EGARCH specifications: γ_2 usually enters equation (3) with a negative sign and bad news ($\varepsilon_t < 0$) causes more volatility than good news ($\varepsilon_t > 0$).

Similarly to GARCH (1, 1) model we incorporate the DOW, WOM and the MOY effects into the volatility equation:

$$\log(h_t) = \gamma_0 + \gamma_1\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma_2\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma_3\log(h_{t-1}) + \sum_{i=2}^{5}\delta_i D_{it} \quad (3.1)$$

$$\log(h_t) = \gamma_0' + \gamma_1'\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma_2'\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma_3'\log(h_{t-1}) + \sum_{i=2}^{5}\delta_i D'_{it} \quad (3.2)$$

$$\log(h_t) = \gamma_0'' + \gamma_1''\left|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right| + \gamma_2''\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \gamma_3''\log(h_{t-1}) + \sum_{i=2}^{12}\delta_i D''_{it} \quad (3.3)$$

Another model used to show the asymmetries described above is threshold GARCH (TGARCH) also known as the GJR-GARCH model following the work of Glosten *et al.* (1993). It extends the classic GARCH model by including a multiplicative dummy to check whether there is a statistically significant difference when shocks are negative. The basic variance equation of the TGARCH (1, 1) model is given by the following equation:

$$h_t = \gamma_0 + \gamma_1\varepsilon^2_{t-1} + \gamma_2 d_{t-1}\varepsilon^2_{t-1} + \gamma_3 h_{t-1} \quad (4)$$

where: d_{t-1} is a dummy variable which takes on value 1 if $\varepsilon_{t-1} < 0$ and zero if $\varepsilon_{t-1} \geq 0$. In this way we deal with good and bad news differently. Good news has an impact equal to γ_1, while bad news has an impact equal to $\gamma_1 + \gamma_2$. If $\gamma_2 > 0$ we can conclude that there is an asymmetry, while if $\gamma_2 = 0$ the news impact is symmetric. The sum $\gamma_1 + \gamma_2$ also measures the persistence of shocks. If the sum is below unit, the shock dies out over time, whilst with a sum close to unit the shock will affect the conditional variance for a certain amount of time. Moreover, if the sum equals to one, the shock will affect volatility for an indefinite time. This is also known as integrated GARCH model or IGARCH.

Including seasonal dummy variables into volatility equation, we get the following relations:

$$h_t = \gamma_0 + \gamma_1\varepsilon^2_{t-1} + \gamma_2 d_{t-1}\varepsilon^2_{t-1} + \gamma_3 h_{t-1} + \sum_{i=2}^{5}£_i D_{it} \quad (4.1)$$

$$h_t = \gamma_0' + \gamma_1'\varepsilon 2t_{-1} + \gamma_2' dt_{-1}\varepsilon^2_{t-1} + \gamma_3' ht_{-1} + \sum_{i=2}^{5}£_i D'_{it} \quad (4.2)$$

$$h_t = \gamma_0'' + \gamma_1''\varepsilon 2t_{-1} + \gamma_2'' dt_{-1}\varepsilon^2_{t-1} + \gamma_3'' ht_{-1} + \sum_{i=2}^{12}£_i D''_{it} \quad (4.3)$$

Finally, our last model of the GARCH family to test is GARCH-M or GARCH-in-mean. Risk-averse investors require a premium as compensation for holding a risky asset, which is a positive function of the risk (*i.e.* the higher the risk, the higher the premium). As Asteriou and Hall (2015) point out, if the risk is captured by the volatility or by the conditional variance, then the conditional variance may enter the conditional mean function. As the risk may be captured by standard deviation as well, we consider the mean and the variance equations as follows:

$$R_t = \pi + v\sqrt{h_t} + \varepsilon_t \tag{5}$$

$$h_t = \gamma_0 + \gamma_1\varepsilon^2_{t-1} + \gamma_2 h_{t-1} \tag{6}$$

where: π, v, γ_0, γ_1 and γ_2 are the coefficients to be estimated. v measures the seasonality in volatility of the market. Seasonal dummy variables will be included into both mean and variance equations, for all the effects surveyed. For the conditional variance equation, concerning the DOW, WOM and the MOY effects will correspond equations 2.1, 2.2 and 2.3, respectively. For the mean equation, we have the following specifications:

$$R_t = \pi + v\sqrt{h_t} + \sum_{i=2}^{5} ¥_i D_{it} + \varepsilon_t \tag{6.1}$$

$$R_t = \pi' + v'\sqrt{h_t} + \sum_{i=2}^{5} ¥_i D'_{it} + \varepsilon_t' \tag{6.2}$$

$$R_t = \pi'' + v''\sqrt{h_t} + \sum_{i=2}^{12} ¥_i D''_{it} + \varepsilon_t'' \tag{6.3}$$

The results will only be reported for specific effects (*i.e.* for the weekend effect, the first-week-of-the-month effect and for the January effect). The errors in these models may be autocorrelated. To eliminate this possibility, we include the lag values of the index return (dependent variable).

The main assumption that underlies the GARCH models is that the conditional distribution of returns is normal, that is, the standard residuals of the models follow a normal distribution. However, this is not always the case in practice, where the tails of even conditional distributions often seem to be fatter than that of the normal distribution. To address this issue, Bollerslev and Wooldrige (1992) introduced quasi-maximum likelihood estimator (QMLE) which will be used in our research to obtain consistent parameter estimators for GARCH models.

In our research we will present the results of the best GARCH model for every country and every seasonal effect in particular. Our selection procedure will be based on Akaike Info Criterion (AIC). Schwarz Info Criterion (SIC) and Log-likelihood will be employed as alternative methods.

4. Empirical Results

4.1 Descriptive Statistics

An examination of the characteristics displayed in Table 1 of the Supplementary Appendix[5] shows that, overall, with the exception of Slovenia, all the average daily returns are positive with the highest value for Romania (0.066%); the value for Slovenia is -0.014%. The lowest returns are observed on Monday for Romania, Latvia, Estonia, Lithuania, Slovakia and Bulgaria, on Tuesday for the Czech Republic and Slovenia, and on Wednesday for Russia, Hungary and Poland while the highest returns are on Monday for Hungary and Russia, on Wednesday for Estonia, on Thursday for Romania, Latvia, the Czech Republic, Poland and Bulgaria and on Friday for Lithuania, Slovakia and Slovenia. From the risk perspective, measured by the standard deviation, the daily returns have the highest risk for Russia and

[5] *Supplementary Appendix is available online http://www.rjef.ro.*

the lowest for Lithuania. Furthermore, Russia has the highest standard deviation on Monday, Tuesday, Thursday and Friday. The daily returns are not normally distributed, with a long left tail are leptokurtic (except Estonia).

Table 2 of the Supplementary Appendix contains descriptive statistics for the weekly returns for each of the markets, that all the weekly mean returns are positive, with the exception of Slovenia, which has a negative return of -0.014%. The highest weekly return is in Romania: 0.067% The highest returns are observed in the majority of the countries in week five (except Bulgaria - week three; Hungary, Lithuania and the Czech Republic - week four) whilst the lowest mean returns are observed in week one for Hungary, the Czech Republic, Poland and Slovenia, in week two for Latvia and Bulgaria and in week three for Romania, Russia, Estonia, Lithuania and Slovakia. The highest risk appears to be for Russia, while the lowest – for Slovakia. However, the weeks with the highest mean returns are not necessary the riskier. Thus, the riskier returns appear generally in week one, except for Slovenia and Bulgaria (in week two), for Hungary and Lithuania (in week four) and for Slovakia (in week five); the lowest mean returns for the greatest bulk of the countries are in week five: Romania, Russia, Estonia, Lithuania and Bulgaria, which seems to be the most advantageous week to invest and to some extend contradicts the modern portfolio theory which suggests that higher returns require higher risk. The majority of return distributions are non-normal, negatively skewed and leptokurtic (peaked).

Table 3 of the Supplementary Appendix exhibits figures similar to the previous two series.

4.2 The Day-of-the-week and the Weekend Effects

Table 2 shows that, with the exception of Hungary, Slovakia and the Czech Republic, the day-of-the-week effect is present in all the countries surveyed. Thus, we have Monday effect in Poland (contrary to what the anomaly suggests), Tuesday effect in Romania and Latvia, Wednesday effect in Romania, Latvia, Estonia, Lithuania, Slovenia and Bulgaria (6 out of 11 countries), Thursday effect in Romania, Latvia and Lithuania and Friday effect in Romania, Russia, Latvia and Estonia. Moreover, Wednesdays and Fridays appear also to have the highest and significant returns among other days of the week. As for the weekend effect, Romania, Latvia, Estonia, Lithuania, Slovenia and Bulgaria have Friday as the day with higher and significant returns than those for Monday. Also, for Latvia, Estonia, Lithuania and Slovenia, the Monday returns are negative and statistically significant, which strengthens our findings regarding this anomaly. However, only for 4 out of 11 countries (namely, Latvia, Lithuania, Slovenia and Bulgaria) we reject the null hypothesis of Wald test.

Further, we test for the existence of the weekend effect in the volatility by allowing the variance to differ across the days of the week by including dummy variables into the variance equation. For Bulgaria, we use GARCH (1, 1) specifications as conditional variances are always positive and not explosive. With small exceptions, all the other days have lower variance than on Monday. Only in the case of Hungary – Wednesday, the Czech Republic – Tuesday and Thursday, Slovakia – Thursday and Slovenia – Wednesday there are days with higher volatility than on Monday. Also, Friday appears to have lower volatility in all countries and this contradicts the Modern Portfolio Theory (MPT) which asserts that there is a trade-off between risk and return and that the investors will gain additional return only taking on additional risk. We have seen that Friday is among the days with the highest and statistically significant returns.

In the case of Lithuania and Slovenia, although we have included 30 lags and 20 lags respectively of the dependent variable into the equation, the residuals are still autocorrelated. However, the results are robust as the autocorrelation and partial autocorrelation do not present big spikes. Also, for Romania, Poland and Bulgaria the residuals present strong ARCH effects up to 30 lags, which indicate that the particular GARCH models were unable to eliminate the heteroskedasticity. This also applies for Latvia, Estonia and Slovakia for specific lags.

The period for which we have investigated the seasonal anomalies, 2000-2015, holds a lot of events which have led to boom or bust periods thus affecting the results. Typically, we would expect much more anomalies during the normal period than during the severe downturn period because the investors are more active in the market and more optimistic. Such an event is the global financial crisis, actually started with the fall of the investment bank, Lehman Brother, on September 15, 2008. Thereby, we deem this date to be the breaking point. We identify weakly significant structural changes only in Romania, Slovakia and Bulgaria by applying the Chow test. Thus, we split the period into two sub-periods: pre-Lehman Brothers and post-Lehman Brothers. The results are exhibited in Table 4 of the Supplementary Appendix. For the post-Lehman Brothers period, Monday appears with negative and statistically significant mean returns for all three countries – which was not the case before the event. Also, for Romania and Bulgaria, Tuesday, respectively Wednesday effects have disappeared. The Friday effect is present for both countries before and after the rise of the crisis. Furthermore, while the weekend effect is not detected before 15 September 2008, it is present in Romania and Bulgaria after the global financial crisis has made the scene.

Table 1

Panel A: Estimation of Return Equation and Volatility – The Weekend Effect

	Romania (TGARCH)	Hungary (TGARCH)	Russia (TGARCH)	Latvia[1)] (TGARCH)	Estonia[2)] (EGARCH)	Lithuania[3)] (EGARCH)	Czech R.[4)] (TGARCH)	Slovakia (GARCH-M)	Poland (EGARCH)	Slovenia[5)] (EGARCH)	Bulgaria[6)] (GARCH)
turn equation											
Constant	-0.000	0.001	0.001***	-0.000**	-0.001***	-0.001**	0.000	-0.002	0.001**	-0.002*	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Tuesday	0.001	-0.000	-0.001	0.001**	0.000	0.001***	-0.001	0.000	-0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Wednesday	0.001	-0.001	-0.001	0.001*	0.001*	0.002*	-0.000	0.001	-0.001	0.003*	0.001*
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Thursday	0.001**	-0.000	-0.000	0.002	0.001	0.001*	-0.000	0.001	-0.000	0.002*	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Friday	0.001**	-0.000	0.000	0.002*	0.001*	0.002*	0.000	0.001	-0.000	0.004*	0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
v	-	-	-	-	-	-	-	0.126***	-	-	-
	-	-	-	-	-	-	-	(0.076)	-	-	-
Return$_{t-1}$	0,116*	0.017	0.011	-0.089*	0.149*	0.082*	0.046*	-0.065*	0.065*	0.248*	0.090*
	(0.021)	(0.017)	(0.017)	(0.020)	(0.020)	(0.025)	(0.016)	(0.019)	(0.016)	(0.052)	(0.021)
Return$_{t-2}$	-	-0.029***	-0.005	0.025	0.041**	0.063**	-0.0088	-	-	-0.055	0.037***
	-	(0.016)	(0.018)	(0.020)	(0.018)	(0.030)	(0.0166)	-	-	(0.033)	(0.020)
Return$_{t-3}$	-	-0.023	-	0.020	-0.019	0.004	-0.013	-	-	-0.060	0.036***
	-	(0.017)	-	(0.018)	(0.021)	(0.022)	(0.020)	-	-	(0.050)	(0.019)
Variance equation											
γ_0	0.000*	0.000	0.000***	0.000	-0.236	-0.164	0.000	0.000	0.062	-0.332*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.144)	(0.270)	(0.000)	(0.000)	(0.098)	(0.128)	(0.000)
γ_1	0.140*	0.042*	0.055*	0.101*	0.264**	0.327*	0.057*	0.052*	0.127*	0.239*	0.156*
	(0.034)	(0.013)	(0.018)	(0.020)	(0.026)	(0.035)	(0.015)	(0.012)	(0.018)	(0.057)	(0.020)
γ_2	0.038*	0.0685*	0.054*	0.033*	-0.017*	-0.042*	0.109*	0.926*	-0.045*	-0.064*	0.848*
	(0.040)	(0.0198)	(0.024)	(0.0298)	(0.026)	(0.031)	(0.0279)	(0.015)	(0.010)	(0.024)	(0.016)
γ_3	0.822*	0.896*	0.897*	0.864*	0.974*	0.944*	0.854*	-	0.985*	0.976*	-
	(0.023)	(0.014)	(0.014)	(0.018)	(0.006)	(0.015)	(0.015)	-	(0.003)	(0.013)	-
Tuesday	0.000*	0.000*	0.000*	0.000*	0.341*	-0.896*	0.000*	0.000*	-0.459*	-0.051*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.216)	(0.352)	(0.000)	(0.000)	(0.163)	(0.212)	(0.000)
Wednesday	0.000*	0.000*	0.000*	0.000*	-0.251*	-0.710*	0.000*	0.000*	-0.291*	0.778*	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.177)	(0.229)	(0.000)	(0.000)	(0.123)	(0.643)	(0.000)

turn equation											
	Romania (TGARCH)	**Hungary** (TGARCH)	**Russia** (TGARCH)	**Latvia**[1)] (TGARCH)	**Estonia**[2)] (EGARCH)	**Lithuania**[3)] (EGARCH)	**Czech R.**[4)] (TGARCH)	**Slovakia** (GARCH-M)	**Poland** (EGARCH)	**Slovenia**[5)] (EGARCH)	**Bulgaria**[6)] (GARCH)
Thursday	**0.000***	0.000*	**0.000***	**0.000***	**-0.155***	**-0.433***	**0.000***	**0.000***	**-0.179***	**-0.897***	**0.000***
	(0.0001)	(0.000)	(0.000)	(0.000)	(0.172)	(0.265)	(0.000)	(0.000)	(0.127)	(0.522)	(0.000)
Friday	**0.000***	**0.000***	**0.000***	**0.000***	**-0.249***	**-0.917***	**0.000***	**0.000***	**-0.539***	**-0.070***	**0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.239)	(0.296)	(0.000)	(0.000)	(0.159)	(0.197)	(0.000)
Log likelihood	12303.350	12019.490	10986.770	12895.440	13604.450	13889.270	12669.190	12790.570	12779.420	7732.101	12221.900
AIC	-5.891	-5.757	-5.261	-6.184	-6.547	-6.684	-6.076	-6.125	-6.120	-6.117	-6.171
SIC	-5.870	-5.733	-5.238	-7.149	-6.481	-6.618	-6.041	-6.104	-6.098	-6.017	-6.136
Wald Test (mean eq.)	7.703	1.215	2.108	**16.563***	**14.200***	**15.815***	2.889	3.637	4.139	**23.201***	**17.953***
Wald Test (var. eq.)	2.215	2.105	7.314	**18.599***	3.423	**12.481****	4.662	**8.160*****	**12.030****	4.117	7.495
Panel B: Autocorrelation Q Statistics											
Lags	**Romania**	**Hungary**	**Russia**	**Latvia**	**Estonia**	**Lithuania**	**Czech R.**	**Slovakia**	**Poland**	**Slovenia**	**Bulgaria**
5	6.915	8.690	4.207	9.223	8.119	**13.833****	2.540	4.656	2.349	**11.530****	3.828
10	9.437	**16.019*****	8.638	10.386	10.087	**27.836***	2.867	8.060	3.996	**17.738*****	8.216
15	20.165	17.360	10.660	19.609	18.249	**31.461***	8.636	**24.376*****	10.889	20.108	19.575
20	24.229	21.036	27.043	23.240	20.086	**36.686***	12.659	27.664	16.270	**33.627****	25.762
30	35.663	30.320	40.048	35.000	28.730	**53.857***	20.848	34.653	30.032	**74.591***	38.446
Panel C: ARCH-LM Tests											
5	**13.832****	3.500	2.263	6.180	**10.039*****	2.226	3.226	0.838	**17.379***	0.740	**16.219***
10	**23.987***	7.922	3.526	11.266	**16.623*****	4.811	4.474	5.979	**19.274****	1.176	**19.865****
15	**26.873****	13.114	4.021	**35.969***	19.716	6.659	11.746	**71.776***	**24.250*****	1.610	**25.911****
20	**30.650*****	17.824	5.973	**41.467***	22.551	7.803	15.080	**74.038***	27.734	1.910	**29.388*****
30	**45.131****	22.673	9.591	**45.084****	**85.805***	12.233	20.512	**88.541***	**41.165*****	2.470	**44.814****

Notes: Standard errors are reported in parentheses.
"*", "**" and "***" denote statistical significance at 1, 5 and 10 level, respectively.
1), 2), 3), 4), 5), 6): We have eliminated the autocorrelation by including 10, 30, 30, 10, 20 and 10 lags, respectively, but we have reported the results only for three lags.
Parameters γ_0, γ_1, γ_2 and γ_3 are, of course, different for each GARCH model in part. We have put them in the same column for space reasons.

Table 2

Results for the Mean Equation

	Days with positive and significant returns	Days with negative and significant returns	Days with returns significantly lower than Monday	Days with returns significantly higher than Monday
Romania	Tuesday, Wednesday, **Thursday**, Friday	-	-	Thursday, Friday
Hungary	-	-	-	-
Russia	Friday	-	-	-
Latvia	Tuesday, Wednesday, Thursday, **Friday**	Monday	-	Tuesday, Wednesday, Thursday, Friday
Estonia	Wednesday, **Friday**	Monday	-	Wednesday, Friday
Lithuania	**Wednesday**, Thursday, Friday	Monday	-	Tuesday, Wednesday, Thursday, Friday
Czech Rep.	**-**	-	-	-
Slovakia	-	-	-	-
Poland	**Monday**, Friday	-	-	-
Slovenia	**Wednesday**, Friday	**Monday**, Tuesday	-	Wednesday, Thursday, Friday
Bulgaria	**Wednesday**, Friday	-		Wednesday, Friday

Notes: In bold we present the day with the highest positive and significant return and with the highest negative and significant return, respectively. We have considered a maximum level of significance of 10%.

4.3 The Week-of-the-month and the First-week-of-the-month Effects

In Table 3 - Panel A, we present the results for both the returns and conditional variance equations for the entire sample. The findings confirm the existence of a distinct week-of-the-month pattern in stock market returns for all the countries of our sample. With the exception of Latvia, which presents the first-week-of-the-month effect (all weeks have lower returns than those reported in the first week, but are indistinguishable from zero, that is, are not statistically significant), all other countries seem to have an opposite pattern: there is at least one week with returns that are higher than those in week one. The most frequent week in this respect is week five. In addition, for Romania, Hungary, Estonia, the Czech Republic, Poland and Slovenia the results are statistically significant. Moreover, in Hungary and Slovenia the mean weekly returns that occur in week four are greater and statistically significant than those from week one. It is worth mentioning that in the case of the Czech Republic, Poland and Slovenia, there are no weeks with the mean returns lower than those in week one.

When it comes to seasonal effects we have found statistically significant effects for all markets. For seven out of the eleven countries, we notice significant and positive effects occurring in week five (namely Romania, Hungary, Russia, Estonia, the Czech Republic, Poland and Bulgaria). Romania, Russia and Bulgaria have no weeks with negative mean returns, while in the case of Latvia, mean returns in week one are positive and significant. However, there is no difference in mean returns across a given month's weeks, according to the Wald test results, except in Hungary, Russia and Poland.

To detect the existence of a week-of-the-month effect in volatility, we allow the conditional variance to change for each week, including weekly dummy variables in the variance equation, with a constant. The results are displayed in the lower part of Panel A, in Table 5. For Latvia and Bulgaria, we use GARCH (1, 1) specifications, conditional variances are always positive and are not explosive. Also, in both cases, the volatility tends to decrease over time, but at a slow rate ($\gamma_1 + \gamma_2$ is very close to unity). Table 3 exhibits that, with the exception of Lithuania and Slovakia, most risky is the first week of the month. In the case of Romania and Hungary, all weeks are less risky than the first one and, on the other hand, week one is the less risky compared to the others in the case of Slovakia.

In Table 3, we also notice that the residuals are affected neither by autocorrelation nor by heteroskedasticity (except for the Czech Republic, Slovakia, and Slovenia, where the autocorrelation is present for specific lags). The week in which Lehman Brothers officially went bankrupt (09/15/2008 – 09/19/2008) is a breaking point in the case of Romania, Slovakia, Slovenia and Bulgaria according to the results of the Chow test for structural changes. Hence, we analyze the week-based anomalies by splitting our sample into two sub-periods.

The week effects have dampened considerably after the Lehman Brothers crash, especially for Slovenia and Bulgaria (Supplementary Appendix, Table 5). In Slovenia, there were three weeks with positive and statistically significant returns before the week 09/15/2008 – Week 1, Week 2 and Week 5 – a strong evidence in favor of weekly effects, but for that period 09/16/2008 – 12/31/2015 there were negative and significant returns (Week 1 and Week 3) and no positive returns. For Romania and Bulgaria, the weeks with positive and significant returns have reduced in the post-Lehman Brothers period, still having Week 5 and Week 4 effects, respectively.

As for the first-week-of-the-month effect, we have discovered little evidence for Slovakia and Slovenia for the pre-Lehman Brothers period, but no evidence for the post-Lehman Brothers period. In Romania and Bulgaria instead Week 5 and Week 4 returns, respectively, seem to be significantly higher than in Week 1.

4.4 The Month-of-the-year and the January Effects

The summary results for both the returns and conditional variance equations for the January effect and seasonality effect, for the entire sample, for different GARCH models, best suited to each particular country are shown in Table 6. With the exception of Slovakia, all the countries exhibit a statistically significant January effect. It appears that the Baltic countries have the highest number of months with returns lower than January (Latvia – 7, but only two are significant Estonia – 11, Lithuania – 8) and that the investors could take advantage of this mispricing and build portfolios that include stocks from these countries. In the case of Romania, December is the only month with higher returns than January and in this case the January effect cannot be explained by the tax-loss selling hypothesis.

As for the seasonal effects (using all seasonal dummies together, without a constant), statistically significant effects exist for all countries. More importantly, for five out of the eleven country cases we have significant effects occurring in January (namely Romania, Hungary Latvia, Estonia and Lithuania). Our findings support to some extent the results of Asteriou and Kavetsos (2006) who found statistically significant patterns in January for Romania, Hungary, Poland and Slovenia, and are inconsistent with those of Heininen and Puttonen (2008) who suggest that there are no signs of monthly abnormalities in nine out of eleven countries from CEE.

Table 3

Panel A: Estimation of Return Equation and Volatility – The First-week-of-the-month Effect

	Romania	Hungary	Russia	Latvia	Estonia	Lithuania	Czech R.	Slovakia	Poland	Slovenia[1)]	Bulgaria
	(TGARCH)	(TGARCH)	(TGARCH)	(GARCH)	(EGARCH)	(EGARCH)	(TGARCH)	(TGARCH)	(TGARCH)	(TGARCH)	(GARCH)
Return equation											
Constant	0.001	0.000	0.001	0.001**	0.001***	0.000***	-0.000	0.000	-0.001	-0.001	0.001
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Week 2	0.000	0.000	-0.001	-0.001	-0.001***	0.000	0.000	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Week 3	0.000	0.000	-0.001	-0.001	0.000	0.000	0.000	0.000	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Week 4	0.000	0.001***	-0.001	0.000	0.000	0.000	0.001	0.000	0.001	0.001***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Week 5	0.001***	0.002*	0.002	0.000	0.000	0.000	0.002***	0.000	0.002*	0.002***	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Return$_{t-1}$	0.051	-	-	0.114**	0.134*	0.020**	0.063	-0.102*	0.078**	0.051	0.157*
	(0.040)	-	-	(0.051)	(0.038)	(0.044)	(0.039)	(0.037)	(0.035)	(0.046)	(0.046)
Return$_{t-2}$	-	-	-	0.052	0.067	0.190*	-	-	-	0.049	0.044
	-	-	-	(0.045)	(0.042)	(0.048)	-	-	-	(0.049)	(0.045)[
Return$_{t-3}$	-	-	-	-	0.052	-	-	-	-	0.098**	0.101*
	-	-	-	-	(0.041)	-	-	-	-	(0.045)	(0.039)
Variance equation											
γ_0	0.000*	0.000*	0.000**	0.000	-0.410	-0.440***	0.000**	0.000	0.000**	0.000**	0.000*
	(0.000)	(0.000)	(0.000)	(0.000	(0.283)	(0.241)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
γ_1	0.154**	0.021	0.093**	0.244*	0.294*	0.261*	0.075	0.164**	0.059***	0.081***	0.109*
	(0.067)	(0.024)	(0.037)	(0.085)	(0.055)	(0.058)	(0.062)	(0.076)	(0.033)	(0.043)	(0.031)
γ_2	-0.021	0.123*	0.067	0.704*	-0.018	-0.020	0.108	-0.040	0.069	0.113	0.879*
	(0.079)	(0.047)	(0.053)	(0.079)	(0.046)	(0.040)	(0.103)	(0.090)	(0.049)	(0.106)	(0.033)
γ_3	0.838*	0.849*	0.837*	-	0.952*	0.983*	0.805*	0.833*	0.856*	0.776*	-
	(0.041)	(0.038)	(0.026)	-	(0.018)	(0.010)	(0.061)	(0.048)	(0.032)	(0.073)	-
Week 2	0.000**	0.000**	0.000	0.000	-0.288	-0.214	0.000***	0.000***	0.000**	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.361)	(0.346)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Week 3	0.000*	0.000**	0.000	0.000	-0.490***	-0.059	0.000**	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.269)	(0.287)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Week 4	0.000**	0.000*	0.000**	0.000	-0.400	0.416	0.000	0.000	0.000*	0.000	0.000*

	Return equation										
	Romania (TGARCH)	**Hungary** (TGARCH)	**Russia** (TGARCH)	**Latvia** (GARCH)	**Estonia** (EGARCH)	**Lithuania** (EGARCH)	**Czech R.** (TGARCH)	**Slovakia** (TGARCH)	**Poland** (TGARCH)	**Slovenia**[1)] (TGARCH)	**Bulgaria** (GARCH)
	(0.000)	(0.000)	(0.000)	(0.000)	(0.324)	(0.423)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Week 5	**0.000*** (0.000)	**0.000*** (0.000)	0.000 (0.000)	0.000 (0.000)	**-0.506***** (0.270)	0.281 (0.319)	0.000 (0.000)	0.000 (0.000)	**0.000***** (0.000)	0.000 (0.000)	**0.000*** (0.000)
Log likelihood	3024.196	3065.745	2861.510	3249.337	3242.135	3359.335	3170.317	3256.508	3192.962	1959.955	2920.533
AIC	-7.219	-7.312	-6.823	-7.768	-7.755	-8.030	-7.569	-7.776	-7.623	-7.706	-7.450
SIC	-7.139	-7.238	-6.749	-7.689	-7.664	-7.945	-7.490	-7.696	-7.544	-7.555	-7.360
Wald Test (mean eq.)	6.680	**716.290***	**7.908*****	3.979	7.652	1.595	3.545	2.372	**7.998*****	7.086	2.195
Wald Test (var. eq.)	**7.496*****	**27.500***	**8.976*****	3.111	4.630	7.375	**11.468****	4.586	**12.228****	4.228	**50.416***
	Panel B: Autocorrelation Q Statistics										
Lags	**Romania**	**Hungary**	**Russia**	**Latvia**	**Estonia**	**Lithuania**	**Czech R.**	**Slovakia**	**Poland**	**Slovenia**	**Bulgaria**
5	6.636	6.523	7.763	4.433	5.957	6.015	7.852	6.340	5.413	0.854	5.622
10	14.350	8.729	11.335	**19.223****	12.063	14.048	12.327	11.286	8.0670	7.323	8.795
15	17.169	12.31	16.048	20.174	18.161	22.021	**24.333*****	12.392	17.500	**23.830*****	16.782
20	21.467	18.539	23.514	23.242	22.532	23.856	25.370	**29.619*****	18.756	26.985	18.705
30	33.433	25.931	33.120	35.000	29.470	33.085	36.296	39.449	23.027	35.711	31.012
	Panel C: ARCH-LM Tests										
5	7.092	0.266	2.804	3.426	3.121	1.572	3.644	3.104	3.157	0.824	2.364
10	9.769	1.585	5.557	4.406	7.642	5.464	5.591	6.925	4.691	6.920	6.415
15	17.684	3.348	8.481	5.919	11.694	7.226	10.331	9.504	7.888	9.621[	8.933
20	22.777	9.414	11.879	7.523	15.871	10.672	12.850	12.260	11.753	12.751	18.523
30	28.874	16.900	17.411	10.087	21.190	18.986	18.699	19.557	18.010	30.346	22.213

Notes: Standard errors are reported in parentheses.

"", "**" and "***" denote statistical* significance *at 1, 5 and 10 level, respectively.*

1): In the case of Slovenia, we have eliminated autocorrelation by including 5 lags of the dependent variable, but we have reported the results only for 3 lags.

Parameters γ_0, γ_1, γ_2 and γ_3 are, of course, different for each GARCH model in part. We have put them in the same column for space reasons.

Table 4

Results for the Mean Equation

	Weeks with positive and significant returns	Weeks with negative and significant returns	Weeks with returns significantly lower than Week 1	Weeks with returns significantly higher than Week 1
Romania	Week 3, **Week 5**	-	-	Week 5
Hungary	Week 4, **Week 5**	-	-	Week 4, Week 5
Russia	Week 5	-	-	-
Latvia	**Week 1**, Week 4	-	-	-
Estonia	Week 4, **Week 5**	-	Week 2	Week 5
Lithuania	-	-	-	-
Czech R.	Week 5	-	-	Week 5
Slovakia	-	-	-	-
Poland	Week 5	-	-	Week 5
Slovenia	Week 4	-	-	Week 4, Week 5
Bulgaria	Week 4, **Week 5**	-	-	-

Notes: In bold we present the week with the highest positive and significant return and with the highest negative and significant return, respectively. We have considered a maximum level of significance of 10%.

Further, to detect the existence of a January effect in volatility, we allow the conditional variance to change for each month, including monthly dummy variables in the variance equation, with a constant. For Russia and Latvia, we use GARCH (1, 1) specifications as conditional variances are always positive and are not explosive in these cases.

For most of the countries the highest volatility occurs in January. Although there are months with a greater risk than January (with the exception of Romania, Russia and Bulgaria) they are not statistically significant. Slovakia is the only country with riskier returns occurring in February. It is worth mentioning that Romania has the highest number of months (6) with lower-than-January returns. The Ljung–Box Q statistics and the ARCH-LM tests for different order (5, 10, 15, 20, and 30 lags) show that, with the exception of Estonia, we fail to reject the null hypothesis of no serial correlation in the residuals for all other countries. The Chow test has confirmed with a significance level of 10 that there are structural changes in the ninth month of 2008 for Romania, Slovakia, Slovenia and Bulgaria. For the period before September 2008, there are months with positive and statistically significant returns for all countries – evidence of the month-of-the-year effect. However, after the collapse of the investment bank, in the case of Romania and Slovakia the monthly effects have completely disappeared; for Slovenia and Bulgaria, we have different months with average returns that are positive and significant.

Testing explicitly for the January effect (regressing the monthly dummy variables, with a constant for January) we came up with mixed results. If before the fall of Lehman Brothers our findings indicate the presence of the January effect in Romania, Slovakia and slightly in Bulgaria, after the event we found stronger evidences of this mispricing in Slovenia and Bulgaria but poorer evidence for Romania and Slovakia, where we have identified months with returns significantly higher than in January.

Thus, the statistical evidence clearly points out the presence of the month-of-the-year effect (January effect) in certain considered countries.

When computing the average cumulative returns (ACRs) based on these anomalies, it appears that for the weekend effect the ACRs are too small to offset the transaction costs (considering them constant over time at a level of 0.5%) for all Eastern European countries we have analyzed. When it comes to the fourth- and / or the last-week-of-the-month effect, Romania is the only country with a potential for arbitrage (ACR of 2.72% for buying in the first week of the month and sell in the last week of the month). As for the January effect, with the exception of Slovakia (ACR of -0.36%) and Poland (ACR of 0.85%), all other markets have a potential for arbitrage opportunities when considering transaction costs. Again, Romania with the ACR of 5.90% seems to be the most profitable from this standpoint.

5. Conclusions and Policy Implications

This study investigates three main seasonal anomalies (in return and volatility – i.e. the day-of-the-week and the weekend effects, the first-week-of-the-month and the week-of-the-month effects and the month-of-the-year and the January effects) employing GARCH models for eleven countries from Central and Eastern Europe. Our findings document strong evidence in favor of predictable patterns for calendar-based anomalies (both in return and volatility). The results come in contradiction with other similar studies which analyze financial market anomalies on developed markets, concluding that the increase in efficiency and liquidity have led to the disappearance of seasonal anomalies in nearly all of the most developed countries (see Gu, 2003).

Thus, one can conclude that these markets are not efficient (the EMH does not hold), giving rise to arbitrage opportunities. The results are to some extent in line with those in literature (*e.g.* Asteriou and Kavetsos, 2006, Diaconaşu *et al*. 2012, Kanaryan *et al*., 2002) but, also, contradict those of Heininen and Puttonen (2008) or Georgantopoulos *et al*. (2011). Also, they seem to be influenced by the period in which we carried out our analysis. However, when considering transaction costs, the only profitable anomaly (in terms of average cumulative returns) seems to be the January effect, which implies buying (price-declined) shares in December and selling them in January. Hence, the investors must not neglect the transaction costs when deciding to take advantage of these anomalies.

Our contribution to the existing literature lies mainly in the sample and period which we have selected – the Central and Eastern European area (mostly frontier and emerging countries), for 16 years and two sub-periods (pre- and post-Lehman Brothers), and also in the anomalies we have dissected: if the day-of-the-week and the month-of-the-year effects have been extensively studied by many researchers, the week-of-the-month anomaly is far less analyzed in the CEE markets. Therefore, through our paper we enrich the academic knowledge in this respect producing also valuable insights for investors, both long-term and speculative.

Table 5

Panel A: Estimation of Return Equation and Volatility – The January Effect

	Romania (TGARCH)	Hungary (EGARCH)	Russia (GARCH)	Latvia (GARCH)	Estonia (EGARCH)	Lithuania (EGARCH)	Czech R. (TGARCH)	Slovakia (EGARCH)	Poland (TGARCH)	Slovenia (EGARCH)	Bulgaria (TGARCH)
Return equation											
Constant	**0.001***	**0.001*****	0.001	**0.002***	**0.003***	**0.002***	0.001	**-0.001****	0.001	**0.001*****	**0.002****
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
February	-0.001	-0.001	-0.001	**-0.002****	**-0.001****	-0.001	0.000	**0.002*****	0.000	**-0.003***	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
March	**-0.002*****	-0.001	-0.001	**-0.002***	**-0.003***	**-0.001*****	-0.001	**0.001*****	0.000	-0.001	**-0.002****
	(0.001)	(0.001)	(0.001)	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
April	0.000	0.000	-0.001	-0.001	**-0.002***	**-0.001****	0.000	0.000	0.000	0.000	**-0.002*****
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
May	**-0.003***	**-0.002*****	**-0.003****	**-0.002***	**-0.004***	**-0.002***	**-0.002*****	0.000	-0.001	-0.001	**-0.002****
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
June	0.000	**-0.0021****	-0.001	0.000	**-0.003***	-0.001	**-0.002****	0.000	**-0.002*****	-0.001	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0006)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
July	0.000	-0.001	0.000	0.000	**-0.002***	**-0.001****	0.000	**0.001****	0.000	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
August	-0.001	-0.001	-0.001	-0.001	**-0.003***	**-0.002***	0.000	**0.002***	0.000	**-0.002****	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
September	-0.001	-0.001	-0.001	**-0.002****	**-0.003***	-0.001	-0.001	0.001	0.000	**-0.002****	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
October	-0.001	-0.001	0.000	**-0.002**	**-0.002***	**-0.002****	0.000	0.000	0.000	**-0.002****	**-0.002****
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
November	**-0.002***	-0.001	-0.001	**-0.001*****	**-0.002***	**-0.002****	0.000	0.001	-0.001	**-0.003***	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
December	0.000	-0.001	-0.001	**-0.001*****	**-0.003***	**-0.002***	0.000	**0.001****	0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Return$_{t-1}$	**0.167***	-	-	-	**0.231***	**0.288***	-	-	-	**0.166***	**0.253***
	(0.046)	-	-	-	(0.076)	(0.046)	-	-	-	(0.045)	(0.061)
Return$_{t-2}$	-	-	-	-	-	-	-	-	-	**0.442***	-
	-	-	-	-	-	-	-	-	-	(0.049)	-
Variance equation											
γ_0	**0.000****	**-4.685****	0.000	0.000	0.418	**-13.900***	0.000	-4.647	0.000	**-9.973***	0.000
	(0.000)	(2.332)	(0.000)	(0.000)	(0.486)	(1.084)	(0.000)	(3.108)	(0.000)	(2.570)	(0.000)

Return equation											
	Romania (TGARCH)	Hungary (EGARCH)	Russia (GARCH)	Latvia (GARCH)	Estonia (EGARCH)	Lithuania (EGARCH)	Czech R. (TGARCH)	Slovakia (EGARCH)	Poland (TGARCH)	Slovenia (EGARCH)	Bulgaria (TGARCH)
γ_1	0.179*** (0.094)	0.406** (0.183)	0.220* (0.066)	0.137* (0.036)	0.372* (0.097)	1.032* (0.147)	0.045 (0.062)	0.538* (0.174)	0.147 (0.093)	-0.947* (0.175)	0.171* (0.053)
γ_2	0.044 (0.121)	-0.157 (0.114)	0.680* (0.073)	0.644* (0.083)	0.025 (0.065)	0.408* (0.120)	0.280*** (0.167)	0.013 (0.121)	0.179 (0.155)	-0.193 (0.132)	0.076 (0.139)
γ_3	0.639* (0.1019)	0.583* (0.181)	- -	- -	1.017* (0.013)	-0.101 (0.083)	0.619* (0.123)	0.625* (0.219)	0.632* (0.105)	0.067 (0.194)	0.627* (0.107)
February	0.000* (0.000)	-0.008 (0.648)	0.000 (0.000)	0.000 (0.000)	-0.181 (0.785)	0.668 (0.453)	0.000 (0.000)	1.188*** (0.638)	0.000 (0.000)	-1.402** (0.698)	0.000 (0.000)
March	0.000 (0.000)	-0.892 (0.581)	0.000 (0.000)	0.000 (0.000)	-1.400* (0.647)	-0.254 (0.495)	0.000 (0.000)	-1.139 (0.879)	0.000*** (0.000)	-0.856 (0.635)	0.000** (0.000)
April	0.000 (0.000)	-0.303 (0.530)	0.000 (0.000)	0.000** (0.000)	-1.049 (0.639)	-0.725 (0.518)	0.000 (0.000)	-0.765 (0.677)	0.000 (0.000)	-0.920 (0.639)	0.000 (0.000)
May	0.000*** (0.000)	-0.131 (0.524)	0.000 (0.000)	0.000 (0.000)	-0.204 (0.564)	-0.280 (0.523)	0.000 (0.000)	0.388 (0.574)	0.000 (0.000)	0.032 (0.610)	0.000 (0.000)
June	0.000*** (0.000)	-0.714 (0.530)	0.000*** (0.000)	0.000 (0.000)	-1.103** (0.557)	-0.566 (0.580)	0.000 (0.000)	-1.710** (0.680)	0.000 (0.000)	-1.167*** (0.600)	0.000 (0.667)
July	0.000** (0.000)	-0.982** (0.494)	0.000 (0.000)	0.000 (0.000)	-0.364 (0.635)	-1.064 (0.653)	0.000 (0.000)	0.185 (0.615)	0.000 (0.000)	-0.870 (0.577)	0.000** (0.000)
August	0.000 (0.000)	-0.368 (0.533)	0.000 (0.000)	0.000 (0.000)	0.268 (0.646)	-0.678 (0.564)	0.000 (0.000)	-0.737 (0.621)	0.000 (0.000)	-1.991* (0.567)	0.000 (0.000)
September	0.000** (0.000)	-1.022*** (0.539)	0.000 (0.000)	0.000 (0.000)	-0.995 (0.655)	0.153 (0.521)	0.000 (0.000)	-0.310 (0.709)	0.000 (0.000)	0.547 (0.635)	0.000 (0.000)
October	0.000 (0.000)	0.067 (0.610)	-0.000*** (0.000)	0.000*** (0.000)	-0.300 (0.743)	0.871 (0.561)	0.000 (0.000)	0.411 (0.705)	0.000 (0.000)	-0.319 (0.682)	0.000 (0.000)
November	0.000 (0.000)	-0.338 (0.570)	0.000 (0.000)	0.000 (0.000)	-0.758 (0.667)	0.505 (0.552)	0.000 (0.000)	0.204 (1.074)	0.000 (0.000)	-1.489** (0.6399)	0.000 (0.000)
December	0.000* (0.000)	-1.543** (0.6862)	0.000 (0.000)	0.000*** (0.000)	-0.222 (0.741)	-1.163* (0.417)	0.000 (0.000)	-2.283* (0.762)	0.000 (0.000)	-1.201*** (0.691)	0.000*** (0.000)
Log likelihood	831.081	849.941	822.450	881.866	875.827	884.136	876.030	912.140	869.680	548.021	794.796
AIC	-8.409	-8.572	-8.296	-8.915	-8.878	-8.965	-8.844	-9.220	-8.778	-9.026	-8.426
SIC	-7.932	-8.114	-7.855	-8.474	-8.401	-8.488	-8.386	-8.762	-8.320	-8.334	-7.933
Wald Test (mean eq.)	42.161*	9.668	11.906	65.299*	122.474*	24.859***	20.352**	16.546	15.310	47.628*	40.413*

Return equation											
	Romania (TGARCH)	**Hungary** (EGARCH)	**Russia** (GARCH)	**Latvia** (GARCH)	**Estonia** (EGARCH)	**Lithuania** (EGARCH)	**Czech R.** (TGARCH)	**Slovakia** (EGARCH)	**Poland** (TGARCH)	**Slovenia** (EGARCH)	**Bulgaria** (TGARCH)
Wald Test (var. eq.)	**69.047***	12.437	**21.685****	17.270	**21.801****	**45.789***	12.502	**43.641***	**47.906***	**31.453***	**27.238**[**
Panel B: Autocorrelation Q Statistics											
5	1.282	8.181	1.892	8.061	4.831	2.419	5.786	7.614	4.176	2.710	5.593
10	3.322	9.916	4.000	11.802	**19.295****	10.586	7.960	13.953	7.621	5.599	6.7754
15	14.545	13.825	7.322	13.009	**22.700*****	13.733	11.936	16.466	12.811	13.642	12.489
20	15.030	15.569	10.901	16.851	24.487	24.680	13.070	26.213	15.888	14.561	12.873
30	35.329	25.578	22.201	30.707	30.138	33.174	27.363	37.076	26.176	23.432	19.714
Panel C: ARCH-LM Tests											
5	3.754	1.727	1.835	4.192	4.614	**15.882***	3.343	5.246	0.411	4.302	**9.694*****
10	5.465	**16.156*****	5.638	8.515	5.426	**21.563****	**22.613****	7.325	7.121	6.912	12.100
15	6.446	17.894	10.913	9.843	13.542	**22.639****	**27.192****	11.180	13.770	11.524	19.384
20	9.830	17.894	15.575	11.721	21.142	**30.717*****	**37.555***	18.117	20.630	11.940	22.855
30	24.234	29.725	24.330	20.760	26.891	36.205	40.122	26.980	27.277	18.079	27.664

Notes: Standard errors are reported in parentheses. "", "**" and "***" denote statistical significance at 1, 5 and 10 level, respectively. Parameters γ_0, γ_1, γ_2 and γ_3 are, of course, different for each GARCH model in part. We have put them in the same column for space reasons.*

Table 6

Results for the Mean Equation

	Months with positive and significant returns	Month with negative and significant returns	Months with returns significantly lower than January	Months with returns significantly higher than January
Romania	**January**, April, July	May	March, May, November	-
Hungary	**January**, April	-	May, June	-
Russia	October	**-**	May	-
Latvia	**January**, April, June, July, August	-	November, December	-
Estonia	**January,** February, April, July, October, November	September, **May**	February, March, April May, June, July, August, September, October, November, December	-
Lithuania	**January**, May, September, November	-	March, April, May, July, August, October, November, December	-
Czech R.	-	June	May, June	-
Slovakia	July, **August**	January	-	February, March, July, August
Poland	March	**-**	May	-
Slovenia	April	February, November	February, August, September, October, November)	-
Bulgaria	July, **December**	**-**	March, April, May, October	-

Notes: In bold we present the month with the highest positive and significant return and with the highest negative and significant return, respectively.
We have considered a maximum level of significance of 10%.

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