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Testing for Seasonal Affective Disorder on Selected CEE and SEE Stock Markets

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Abstract: Effects of seasonal affective disorder (*SAD*) are explored on several selected Central and South East European markets in this study for the period 2010–2018. Both return and risk sensitivities on the *SAD* effect are examined for 11 markets in total (Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Hungary, Poland, Serbia, Slovakia, Slovenia, Romania and Ukraine). *SAD* effects are based upon psychiatric and behavioural theories, and are rarely observed on the stock markets today. Thus, this research provides empirical evaluation of the mentioned effects for some of the markets for the first time in the literature. The results indicate that 6 out of 11 markets exhibit *SAD* effects to some extent, meaning that investors' risk aversion does change over the year, depending upon the season of the year. Such results have consequences in finance theory modelling and practical usage in investment strategies on stock markets as well.

Keywords: behavioural finance; seasonal affective disorder; market blues; seasonality

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1. Introduction

In the last decade, the link between investors' psychological state and the weather and nature effects has been observed more closely. Such research is an extension of behavioural and psychiatry research from late 1980s which focused on effects of weather and seasonality changes on peoples' mood and behaviour. Research dates to papers of Rosenthal et al. (1984), in which clinical studies were made on a sample of 29 people which exhibited a bipolar affective disorder (having different behaviour and mood swings during the fall and winter time); Rosenthal et al. (1987) who found that people had difficulties of concentrating themselves, lack of energy, difficulties of waking up in the morning during the reduced daylight hours days of the year; and Schwarz and Clore (1983) who found that people have tendencies to rate general life satisfaction on a greater level when days are sunny compared to cloudy or rainy days. Other details on the human behaviour in general during the fall and winter time can be found in famous books of Rosenthal (1998, 2012), where, in essence, conclusions arise that people are more depressed as days get shorter. Based upon research, the term Seasonal Affective Disorder (*SAD*) has been coined and defined as depressive disorder of people in fall and winter months with normal behaviour in the rest of the year (Rosenthal 2012). In early 2000s, research on stock markets has started to focus on the *SAD* effects on investors and their behaviour on the markets. The initial study of Kamstra et al. (2003) was the first to empirically evaluate such effects on different stock markets over the world and authors found prominent and robust *SAD* effects.

The basic idea is based upon the experimental research in the field of psychology, in which people were asked to rank the risk-taking propensity (or risk aversion) of financial possibilities. These rankings were correlated with the level of depression of a person (Zuckerman 1984; Wong and Carducci 1991). Thus, empirical work showed that depression which was a result of shorter days during the calendar year is translated to greater risk aversion of individuals. Kamstra et al.'s (2003) research utilized those results into the formation of formal relationship between seasonal patterns of day length and stock market returns. Since investors become more risk averse during the fall and winter months (as daylight shortens), they demand greater returns of riskier financial instruments; thus generating pressures on the stock market on price increase. Research on individual investor level has provided more evidence on the *SAD* effects when making financial decisions: Dolvin et al. (2009) obtained results that investors make more pessimistic forecasts during the *SAD* months of the year; with greater *SAD* effects prominent for geographical locations which are further north. Kliger and Levy (2008) researched investor's probability weighting functions on individuals and found that *SAD* effects are distorting those functions when making financial decisions. The research on the relationship between *SAD* effects and stock market returns has started to spread in the last decade. Most of this research is focused on more developed markets (as it will be seen in the following section). Existing literature is scarce on observing mentioned effects on the Central and Eastern European (CEE) and South-Eastern European markets (SEE). If *SAD* effects are found to be a significant factor which influences the stock returns variation over time, this has consequences in finance model theory and investors' practice and trading strategies. Moreover, there are other impactful consequences if such anomalies in investor behaviour exist, regarding the Efficient Market Hypothesis (EMH). Namely, ever since Fama (1965, 1970) developed this concept, the EMH has been a subject of criticism for decades. The majority of the finance models today assume that EMH holds, with rational behaviour of all of the market participants, especially the asset pricing models which are often used to valuate stocks. However, many empirical and theoretical work today exists which has shown that the assumptions such as the EMH cannot hold, at least in its weak form. The most known critics today are the behavioural economists and in finance the most prominent names are Kahneman and Tversky with prospect theory (see (Shleifer 1999) for details).

Thus, the purpose of this research is to examine if *SAD* effects exist on selected CEE and SEE markets[1]. When writing this research, to the knowledge of the author, there existed only several relevant related papers on this topic. Thus, the purpose is to fill the gap in the literature to observe if investors' risk aversion changes over the year on the selected markets. In that way, initial information could be obtained on the selected markets. Compared to the existing research, this paper observes the *SAD* effects for the first time in the literature for some markets, and the analysis in this research is extended to the *SAD* effects on the risk as well. Based upon the results in this study, further recommendations and other research directions could be made; especially regarding the (rational) finance models which usually do not take into account human behaviour and mood and that they change over time, which affects the estimation results and forecasts. The paper is structured as follows. Section 2 gives an overview of the previous related research. The methodology of this study is explained in the Section 3. Afterwards, the results of the empirical research are given in Section 4 with a discussion in Section 5. Section 6 concludes the research.

2. Previous Research

Previous research on the topic of *SAD* effects on investors is relatively scarce. This is especially true when this topic is compared to literature which tries to explain return anomalies on stock markets via calendar effects, or similar tests of the Efficient Market Hypothesis. Since literature related to this study belongs to the broad term of testing EMH; here we mention some of the newer previous results of testing the inefficiencies of the markets observed in this study. In that way, the results in this paper can be compared to the general conclusions of (in)efficiencies of those markets. Kršikapa-Rašajski and Ranov (2016) applied the typical methodology of observing autocorrelations and ADF testing of the index and return series of BELEX (Serbian market, period: October 2005–December 2014). The authors concluded that a weak form of market efficiency is not found. This means that in this research, some *SAD* effects could be found in the Serbian market. Tokić et al. (2018) observed 4 markets which are included in this study: Croatia, Serbia, Slovenia, and Slovakia (from January 2006 until December 2016) and found that all markets except the Serbian were found to be

[1] The classification of countries being as CEE or SEE countries in this research is based upon the OECD (2018) classification.

weak form efficient. The methodology used in the study is similar to the previous mentioned paper. Croatian market was found to be inefficient in Šonje et al. (2011), especially after the last financial crisis of 2008. Milošević Avdalović and Milenković (2017) applied panel data analysis on Serbian, Bosnian, Croatian, Romanian, and Bulgarian markets (with the Macedonian and Montenegrin) in order to evaluate if the weak form of EMH holds in those markets (in the period from 2008 to 2014). All of the markets were found to be inefficient in the observed period, with presence of calendar anomalies. The Polish stock market was found to be inefficient as well, in the period 2000–2014 in Kilon and Jamroz (2014) by using unit root and autocorrelation tests; whilst non-linear unit root tests were performed in Hasanov and Omay (2007) on stock indices of Bulgarian, Czech, Hungarian, and Slovakian markets which were found to be inefficient (in period with ranging initial date from 1991 until end of 2005). Anghel (2015) focused on the Romanian market in 2013 and different technical analysis approaches of trading strategies on this market, with Superior Predictive Ability test of Hansen and several other testing procedures. The author did find weak form of inefficiencies in the spirit of EMH on the Romanian market. The Ukrainian market was found to be inefficient in Mynhardt and Plastun (2014). Thus, it can be seen that some inefficiencies exist on these markets, which means that *SAD* effects could be a potential reason for those deviations from the EMH.

Most early work in the spirit of this paper is those papers in which authors observed effects of the weather in general on the investor’s mood and behaviour. Saunders (1993) observed and found significant effects of cloudiness in New York on the stock market returns (for the period 1927–1989) and author concluded that investors are irrational to some degree. Hirshleifer and Shumway (2003) focused on 26 different countries in their research (period from 1982 until 1997) and established that sunshine has strong significant correlation with stock returns, a result which is contrary to the rational price models. Cao and Wei (2005) focused on developed stock markets (US, Canada, Britain, Germany, Sweden, Australia, Japan, and Taiwan) for a long time period from 1962 to 2001 in order to evaluate if relationship exists between the temperature and stock returns. The results indicated existence of statistically significant negative correlation between the temperature and stock returns, which was robust to different control variables in the study. Thirty-seven different countries over the world were examined in Dowling and Lucey (2008) with GARCH[2] methodology in order to allow for risk variation over time. The authors found significant weather effects (precipitation, wind, temperature) on stock returns, with greater effects on those markets which were more distanced from the equator. The conclusion of the paper was that *SAD* and lower temperatures affect the equity pricing the most in the analysis. Dolvin et al. (2009) focused on biases of stock analysts and their earnings forecast and how *SAD* affects those forecasts. On a sample of analysts over different geographical latitudes, the authors find that generally, analysts are optimistic in forecasts. However, this optimism is lowered in *SAD* months. Those analysts who lived in north were impacted by the *SAD* effects to a greater extent.

Initial public offerings (IPOs) were in the focus of several analyses as follows. Dolvin and Pyles (2007) collected data for IPOs from 1986 until 2000 and compared the differences between the IPOs in spring and summer with those in fall and winter. With included controls for the firm and offer characteristics in the analysis, the authors found that IPOs are underpriced in the *SAD* months and suggest that those firms who are more flexible could avoid IPOs during those months in order to reduce the cost of issuance. Kliger et al. (2012) looked into *SAD* effects on IPO performances for more than 1500 IPOs in the period from 1975 until 1984 on NASDAQ, American, and NYSE exchanges. The results indicated that IPOs during the fall and winter months earn less returns compared to longer daylight days in the year. Lu and Chou (2012) is a study of the Shanghai stock exchange in which the authors observed effects of the *SAD* and changes in people’s mood on the prices, returns, and liquidity. Although the authors did not find effects on the prices and returns, the *SAD* effects were found on the market liquidity. Dolvin and Fernbaher (2014) extended the analysis to young firms when doing IPOs during *SAD* months and found that such types of firms experience even greater underpricing compared to other firms. Keef et al. (2015) also extended the existing literature on IPOs

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2 Generalized AutoRegressive Conditional Heteroskedasticity.

by observing several sub samples of the total observed period in the analysis. The authors found that during the 1981–1989 and 1999–2000 periods, *SAD* had negative effects on the first trading day returns. These effects were not significant during the 1990–1998 and 2001–2007 periods.

Work mostly related to this study includes the following results. Kamstra et al. (2000, 2002) focused on the daylight-savings time changes and its influence on the weekend (Monday) and resulting effects on return of several international stock exchanges. The authors found that the magnitudes of the daylight-savings effect are approximately from 200 to 500% greater than regular Monday effects, which is an additional explanation of the weekend calendar anomaly in stock returns. Kamstra et al. (2003) was the first extensive research on the aforementioned *SAD* effects on stock return. This paper formally introduced the *SAD* variable in the analysis of return prediction as normalized hours of night. The empirical part of the study observed the Australian, Canadian, New Zealand, US, South African, Swedish, UK, German, and Japanese markets for an extensive period of time (for some markets data was obtained from 1928, until 1991). The results showed that the *SAD* variable affected the return series across the observed markets, with the inclusion of control variables of Monday and January effects. Stefanescu and Dumitriu (2011) focused on the Bucharest stock market by observing the period January 2002 to September 2011 and dividing it into two sub periods in order to investigate whether *SAD* effects on stock returns change over time with respect to the financial crisis of 2008. The first sub period was before the financial crisis (until September 2008) and the second referred to the crisis period (September 2008–September 2011). The *SAD* effects were found to be significant on the Bucharest market, with greater effects being before the financial crisis. However, this research did not include any control variables in the analysis. Murgea (2016) is another study of the Bucharest stock market, in which author observed the period from 2000 to end of 2014 and divided the sample into three sub periods (the first until June 2007; the second from June 2007 until October 2012; and the last from October 2012 until end of 2014). The research is similar to that of Stefanescu and Dumitriu (2011); however, Murgea (2016) added January effect as a control variable in the model. Results indicated that *SAD* effects exist in the Bucharest market in calm periods and in the growth periods as well, but were insignificant in crisis periods. Xu (2016) observed UK financial markets. The author found a significant relationship between the *SAD* effects and return series (for the period February 1988 to December 2011) for different stock and bond portfolios.

Kaplanski and Levy (2017) is a study which focused on the effects of *SAD* on the volatility on seven different markets. The authors controlled the results for macroeconomic fundaments, periodical release of accounting reports, and other calendar anomalies in the return and risk series and found significant effects of the *SAD* variable in the analysis. Škrinjarić et al. (2018) examined the Croatian stock market and several specifications of the model developed in Kamstra et al. (2003), with addition of the *SAD* variable in the Merton's (1973) conditional CAPM model for the period from January 2010 until May 2018. The authors controlled the results with Monday and tax-selling effects and found that *SAD* affects Croatian investors, especially during the fall time, meaning that asymmetric effects exist in the mentioned market.

In conclusion, the effects of weather, changes in daylight hours, and environmental factors were found in different stock markets over the world. The majority of the research checks the robustness of the results by adding control variables in the analysis. More evidence is found over the years in different markets, which could be interpreted as being persistent over time. However, research on markets in development is scarce compared to more developed ones. In that way, this research can fill the existing gap by getting initial insights into the relationship between the *SAD* effects and stock returns on selected CEE and SEE markets, which are still in development.

3. Methodology

The description of methodology in this section is following Kamstra et al. (2003). In order to measure the *SAD* effects on a stock market, the *SAD* variable is defined as photoperiod as follows:

$$SAD_t = \begin{cases} H_t - 12, & \text{if } t \text{ in fall and winter} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

where H_t is defined in spherical trigonometry:

$$H_t = \begin{cases} 24 - 7.72\arccos\left(-\tan\left(\frac{2\pi\delta}{360}\right)\tan\lambda_t\right), & \text{Northern hemisphere} \\ 7.72\arccos\left(-\tan\left(\frac{2\pi\delta}{360}\right)\tan\lambda_t\right), & \text{Southern hemisphere} \end{cases} \tag{2}$$

λ_t is the sun's declination angle at geographical latitude δ; $\lambda_t = 0.4102\sin\left(\frac{2\pi}{365}\left(D_t - 80.25\right)\right)$ and D_t is the day of the year; ranging from 1 to 365 or 366 (depending upon the year being lap year or not). It can be seen that in the first step the daily hours of daylight are calculated via Equation (2) and the *SAD* variable is then calculated by Equation (1), where 12 h are representing the average number of hours of night at a location over the whole year. The *SAD* variable is only defined for the fall and winter months; it is zero otherwise. Thus, the variable *SAD* should capture the heightened risk aversion during the fall and winter months in the following equation:

$$r_t = \mu + \beta_{SAD} SAD_t + \varepsilon_t \tag{3}$$

where r_t denotes return at time t and the error term is denoted with ε_t. The value of β_{SAD} should be positive if *SAD* effects are present in return series. As Kamstra et al. (2003) explained, the *SAD* variable represents the length of night in fall and winter months and the depression associated with fall and winter months leads to higher risk aversion during that time; which leads to positive relationship between the *SAD* variable and return series. In that way, greater returns are demanded by investors to compensate the higher risk aversions during fall and winter months. Moreover, the length of daylight is used, not the changes of daylight, as previous medical studies showed that the length of the daylight affects decision making and mood, not the change itself.

However, if some asymmetry exists in the risk aversion behaviour, an additional variable is defined, which captures the changes of risk aversion before the winter solstice, *FALL* as follows:

$$FALL_t = \begin{cases} SAD_t, & \text{for } t \text{ in fall} \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

In order to allow for a bit smoother transition from the last day of summer to the first day of fall, the *FALL* variable in (4) will be redefined for those two days as a moving average value[3].

Now, Equation (3) can be extended with the *FALL* variable as follows:

$$r_t = \mu + \beta_d d_t + \beta_{SAD} SAD_t + \beta_{FALL} FALL_t + \varepsilon_t \tag{5}$$

where d_t is a binary variable equal to unit value in fall and zero otherwise.

The value of β_{FALL} should be negative if asymmetric effects exist in investor's risk aversion around the winter solstice (see Palinkas et al. 1996). Since return series often exhibit autocorrelation, additional terms can be added in Equation (5) in order to capture the correlated effects. Moreover, control variables should be added in (5), such as the weekend (or Monday) effects and tax-loss selling effects. Thus, the Equation (5) will be augmented as follows:

$$r_t = \mu + \beta_d d_t + \beta_{SAD} SAD_t + \beta_{FALL} FALL_t + \sum_{i=1}^{p} \rho_i r_{t-i} + \sum_{i=1}^{q} \varphi_i \varepsilon_{t-i} + \beta_{MON} MON_t + \beta_{TAX} TAX_t + \varepsilon_t \tag{6}$$

where ARMA[4](p,q) terms could be added if returns exhibit such behaviour, *MON* is a binary variable equal to unit value if t is on Monday and zero otherwise. *TAX* is a binary variable equal to unit value if t is equal to the last day of the tax year and the first four of the next year and zero otherwise. Equation (6) can be estimated with the least squares method and White (1980) corrected errors due to the heteroskedastic nature of return series. Thus, an additional model will be observed in the study,

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[3] This additional redefinition is suggested by one reviewer and the results will be provided for the variable defined in (4) with the smoothing out of the two mentioned days.

[4] AutoRegressive Moving Average.

by estimating Equation (6) for the return equation and a GARCH(p,q) model for the risk equation and additional terms for *SAD* and *FALL* variables in the risk equation, by applying the Maximum Likelihood method of estimation:

$$\sigma_t^2 = \alpha_0 + \alpha_{SAD} SAD_t + \alpha_{FALL} FALL_t + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 \tag{7}$$

Moreover, in the empirical part of the research, additional GARCH models will be observed to see if other specifications describe the data better: the E-GARCH model:

$$\log \sigma_t^2 = \alpha_0 + \alpha_{SAD} SAD_t + \alpha_{FALL} FALL_t + \sum_{i=1}^{p} \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{i=1}^{q} \beta_i \log \sigma_{t-i}^2 + \sum_{i=1}^{r} \gamma_i \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \tag{8}$$

T-ARCH model:

$$\sigma_t^2 = \alpha_0 + \alpha_{SAD} SAD_t + \alpha_{FALL} FALL_t + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^2 + \sum_{i=1}^{r} \pi_i \varepsilon_{t-i}^2 \Gamma_{t-i} \tag{9}$$

where $\Gamma_{t-i} = \begin{cases} 1, \text{ if } \varepsilon_{t-i} < 0 \\ 0, \text{ otherwise} \end{cases}$; P-ARCH model:

$$\sigma_t^\tau = \alpha_0 + \alpha_{SAD} SAD_t + \alpha_{FALL} FALL_t + \sum_{i=1}^{p} \alpha_i \left(\left| \varepsilon_{t-i} \right| - \theta_i \varepsilon_{t-i} \right)^\tau + \sum_{i=1}^{q} \beta_i \sigma_{t-i}^\tau \tag{10}$$

where $\tau > 0$, $|\theta_i| \leq 1$ for $i \in \{1, 2, \ldots, r\}$ (r refers to order of the asymmetry), $\theta_i = 0 \;\; \forall \;\; i > r$ and $r \leq p$; and finally, C-GARCH(1,1) model:

$$\sigma_t^2 = m_t + \alpha_{SAD} SAD_t + \alpha_{FALL} FALL_t + \alpha_1 \left(\varepsilon_{t-1}^2 - m_{t-1} \right) + \beta_1 \left(\sigma_{t-1}^2 - m_{t-1} \right) \tag{11}$$

where the time varying long-run volatility is modeled as: $m_t = \omega + \xi \left(m_{t-1} - \omega \right) + \psi \left(\varepsilon_{t-1}^2 - \sigma_{t-1}^2 \right)$. Details on the family of GARCH model, their estimation and full interpretations can be found in Tsay (2002) or Francq and Zakoian (2010).

4. Empirical Analysis

For the purpose of the empirical analysis, daily data on closing values of stock indices of CEE and SEE countries as OECD (2018) classification; BELEX, BETI, BIRS, BUX, CROBEX, SBITOP, PX, SAX, SOFIX, PFTS, and WIG[5]; were collected from Thompson Reuters, for the period 4 January 2010 until 18 July 2018. Returns for each series were calculated as continuous returns. Descriptive statistics for each return series is shown in Table 1. It can be seen that on average, BUX and PX had greatest returns, with greatest losses occurring in BIRS. The PFTS had the greatest risk in terms of standard deviation, with the greatest positive skewness in the sample. PX index had the smallest value of kurtosis. The sample size (N) varies for each index, due to trading days in each country.

5 The indices refer to the following countries: Serbia, Hungary, Bosnia and Herzegovina, Bulgaria, Croatia, Slovenia, Czech Republic, Slovakia, Romania, Ukraine and Poland respectively.

Table 1. Descriptive statistics for return series in the analysis.

Descriptive Statistics	BELEX	BETI	BIRS	BUX	CROBEX	SBITOP	PX	SAX	SOFIX	PFTS	WIG
Mean return	9.4×10^{-5}	0.0002	−0.0002	0.0003	-7.5×10^{-6}	-2.2×10^{-5}	0.0003	0.0002	0.0002	−0.0001	0.0002
Max return	0.0822	0.1056	0.0384	0.1067	0.0856	0.0372	0.0522	0.0911	0.0563	0.2443	0.0457
Min return	−0.0741	−0.0876	−0.0416	−0.0698	−0.0311	−0.0605	−0.0530	−0.0932	−0.0473	−0.1137	−0.0624
Standard deviation	0.0078	0.0104	0.0069	0.0125	0.0066	0.0087	0.0115	0.0110	0.0081	0.0149	0.0098
Skewness	−0.0620	0.0503	−0.2858	0.1022	0.8042	−0.3894	−0.0864	−0.5064	−0.1367	2.0834	−0.6271
Kurtosis	16.140	16.982	9.8781	7.7799	18.462	6.6837	4.8272	12.993	7.9053	47.169	7.3148
N	2099	2083	2082	2064	2051	2049	2070	1981	2046	2018	2058

Source: author's calculation.

Next, Equation (6) was estimated for each country via the LS method and White (1980) corrections of standard errors. The results are shown in Table 2. The *FALL* variable in Table 2 is used as defined in (4), with the additional smoothing out as stated in the methodology section. Since some of the return series exhibited autoregressive behaviour, AR and/or MA terms were added up to third lags in order to obtain uncorrelated residual series from each model. Gray rows refer to the values of most interest for each country, the *SAD* and *FALL* effects, with bolded significant coefficients. Firstly, it can be seen that with the exception of BIRS, all of the *SAD* betas were positive. This means that on the rest of the markets, changes in investors' risk aversion over year exists and investors become more averse towards risk in the fall and winter time. However, the evidence is significant only for BELEX, BETI, CROBEX, SAX, SOFIX, and PFTS. The greatest changes occur in the Hungarian market (greatest value of the estimated parameter, BETI column). Thus, investors in the Hungarian market demand higher return for bearing the same amount of risk during fall and winter time, when compared to other markets in the sample. The results regarding changing preferences are not surprising, due to previous literature finding that some irrational behaviour exists on the CEE and SEE markets: Filip et al. (2015) found that investors in the Czech, Hungarian, Romanian, and Bulgarian markets exhibit herding behaviour, whilst the Polish investors do not. Such behaviour could contribute to effects of *SAD* variable as observed in this research. Moreover, Todea and Zoicas-Ienciu (2008) by using window-test procedure of Hinich and Patterson found that Hungarian, Czech, Slovakian, Polish, and Romanian markets exhibited windows of rejecting the random walk hypothesis. Since episodes of such behaviour exist on those markets, it is not unusual to expect that investors' preferences change on such markets. Another explanation of such behaviour is found in the Eurodebt crisis on some of the markets in this study which are part of EU, see Ferreira (2018). Ferreira (2018) found that Czech and Polish markets to be more efficient compared to other ones in the study by using the detrended fluctuation analysis approach. Moreover, another interesting approach of examining market inefficiencies was provided in Gajdka and Pietraszewski (2017). In that paper, the authors use Robert Shiller's approach of comparing volatilities of stock prices with volatilities of their fundamental values in the present value of dividend model. Only the Polish market was found to be efficient in those terms, which confirms the results in Table 2.

Table 2. Estimation results of Equation (6), bolded values indicate significant *SAD* and/or *FALL* effects.

Estimated Values/Diagnostics	BELEX	BETI	BIRS	BUX	CROBEX	SBITOP	PX	SAX	SOFIX	PFTS	WIG
$\hat{\beta}_0$	−0.0002 (0.365)	0.0001 (0.705)	-1.8×10^{-5} (0.932)	-6.7×10^{-5} (0.863)	1.2×10^{-5} (0.953)	-8.71×10^{-5} (0.767)	0.0004 (0.218)	−4.2 × 10 (0.865)	1.1×10^{-5} (0.961)	−0.001 (0.257)	-3.9×10^{-5} (0.903)
$\hat{\beta}_{JAN}$	−0.0004 (0.714)	−0.0013 (0.237)	0.001 (0.388)	0.001 (0.293)	0.001 (0.371)	0.0001 (0.903)	−0.003 (0.041) **	−0.001 (0.161)	0.001 (0.574)	−0.002 (0.120)	0.0002 (0.868)
$\hat{\beta}_{MON}$	−0.0011 (0.018) **	−0.0015 (0.028) **	−0.0012 (0.001) ***	0.001 (0.486)	−0.002 (0.000) ***	−0.001 (0.005) ***	−0.001 (0.238)	−0.0002 (0.786)	−0.001 (0.095) *	0.0003 (0.741)	0.0005 (0.395)
$\hat{\beta}_d$	0.0004 (0.565)	0.0005 (0.644)	0.001 (0.085) *	0.002 (0.122)	0.0004 (0.583)	0.002 (0.060) *	0.001 (0.647)	0.001 (0.609)	−0.001 (0.323)	−0.002 (0.107)	0.001 (0.342)

$\hat{\beta}_{SAD}$	**0.0007 (0.017)** **	**0.0012 (0.000)** ***	−0.0002 (0.569)	4.4 × 10^{-5} (0.903)	**0.001 (0.009)** ***	0.0002 (0.361)	0.0003 (0.311)	**0.001 (0.035)** **	**0.001 (0.082)** *	**0.001 (0.003)** ***	0.0002 (0.466)
$\hat{\beta}_{FALL}$	−0.0004 (0.331)	**−0.0014 (0.006)** ***	−0.0003 (0.498)	−0.001 (0.246)	−0.001 (0.165)	−0.001 (0.101)	−0.0004 (0.462)	**−0.001 (0.098)** *	−0.001 (0.666)	−0.0002 (0.711)	−0.0005 (0.228)
$\hat{\rho}_{i-1}$	0.1364 (0.049) **	-	-	-	−0.680 (0.000) ***	0.052 (0.101) *	-	0.677 (0.000) ***	0.112 (0.125) ***	0.089 (0.544)	0.070 (0.027) **
$\hat{\rho}_{i-2}$	-	-	-	-	-	-	-	0.105 (0.002) ***	−0.864 (0.000) ***	-	−0.065 (0.023) **
$\hat{\varphi}_{i-1}$	-	-	-	-	0.743 (0.000) ***	-	-	−0.859 (0.000) ***	−0.080 (0.343)	0.192 (0.162)	-
$\hat{\varphi}_{i-2}$	-	-	-	-	-	-	-	-	0.825 (0.000) ***	-	-
Log L	7219.236	6547.400	7400.540	6118.230	7414.094	6806.999	6305.740	6148.587	6942.737	5704.660	6596.616

Note: *p*-values are given in parenthesis and are calculated based upon White (1980) heteroskedasticity-consistent t-statistics. *, **, and *** denote statistical significance on 10%, 5%, and 1%. The ARMA(1,1) addition to the PFTS returns was included as in that way the residuals of the model became uncorrelated although the AR and MA effects were not significant in the return equation. Please see details for CROBEX, SAX, and SOFIX in Appendix A table, the results should be taken with some caution. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects. Source: author's calculation.

The parameter referring to the *FALL* variable is negative for all of the indices. In that way, it could be said that some asymmetry exists around the winter solstice in the behaviour of investors as well. These effects are significant only for BETI and SAX though. Although some of the parameters are not significant whether we observe the *SAD* or *FALL* betas, their values are very close one to another from one country to another. This is due to all of the markets being close (similar geographical width). However, as it can be seen, some differences do exist (some parameters are significant, whilst others are not).

Calendar effects, as most famous anomalies in stock return series, were not found to be significant on majority of the markets, with PX exception for the January effect and several markets for the Monday effects (BELEX, BETI, BIRS, CROBEX, SBITOP, and SOFIX). Since some effects do exist to an extent, it is recommended for future work to include them as control variables. This is also in accordance with previous literature finding majority of these markets being inefficient and calendar anomalies being present even today on those markets (for more details see (Stoica and Diaconasu 2011) or (Andries et al. 2018) for a newer discussion). Some possibilities exist for short term exploitation of them in order to beat the market with abnormal returns based upon such strategies. However, this is not the focus of this research. Although, it can be seen that regardless of the calendar effects being significant, the existence of *SAD* and/or *FALL* effects do not depend upon the calendar effects.

Next, additional models were estimated by allowing the risks to vary over time by adding the GARCH component in the modelling process, as defined in Equations (7)–(11). The results are shown in Table 3. Now, not only the *SAD* and *FALL* effects are included in the return equation, but they are included in the risk equation as well. However, detailed results on the GARCH modelling is provided in Tables A1–A11 in the Appendix A, with only *SAD* and *FALL* effects being included in Table 3. The selected GARCH model for each index is stated in the last row. Some of the countries exhibited strange behaviour of return and/or volatility series (such as CROBEX, SOFIX and SAX). Previous literature comments such behaviour as non stable due to being emerging markets (see, e.g., Hassan et al. 2006). That is why those results should be taken with some caution[6]. When comparing the estimated values of the mentioned effects in the return series with the results from previous table, it can be seen that the results are very similar for the majority of the markets. This is true, both for the signs of the estimated values and their intensity. When looking at the effects of *SAD* and *FALL* on the risks in the GARCH equations, the *SAD* effects are only present in BUX, SAX, and SOFIX. However, by looking at the values of the estimated parameters, the effects are very minor on the risks on those markets. Volatilities are in that way affected by the *SAD* effects in a very small manner. This is consistent with a somewhat similar research of Dumitriu and Stefanescu (2018) for the Hungarian market, in which no *SAD* effects were found in the period 1996–2006. Future work can focus on examining other possibilities of different functional relationship between the *SAD* variables and the time varying risks of stock returns. This is especially true for CROBEX, SOFIX, and SAX indices, due to somewhat strange behaviour of some of the parameters in return/risk equations. For example, the AR terms in all three return equations have great magnitudes of their coefficients. This means that great persistency is present in those returns (if positive coefficients) or great oscillating behaviour (if negative)[7]. Moreover, the intensity of the GARCH parameters regarding their respective parameters seems not to affect the *SAD* and/or *FALL* effects as well. It can be seen that some markets exhibit higher values of respective parameters, with significant *SAD* effects, and some markets have very small values of those parameters but have significant *SAD* effects as well. It seems that regardless of the varying risk of stock returns, the effects of daylight hours on the returns stay the same.

Table 3. Estimation results of model (6) with GARCH specifications.

Estimated Values/Diagnostics	BELEX	BETI	BIRS	BUX	CROBEX	SBITOP	PX	SAX	SOFIX	PFTS	WIG
$\hat{\beta}_0$	0.0001 (0.569)	0.0004 (0.116)	−4.4 × 10^−5 (0.971)	0.0004 (0.278)	0.0004 (0.026) **	7.3 × 10^−5 (0.754)	0.0005 (0.112)	−8.7 × 10^−5 (0.774)	0.0003 (0.358)	−0.0003 (0.109)	0.0003 (0.291)
$\hat{\beta}_{JAN}$	−0.001 (0.283)	−0.001 (0.107)	0.001 (0.097) *	0.001 (0.539)	0.0003 (0.699)	−0.0004 (0.631)	−0.001 (0.274)	−0.001 (0.262)	1.4 × 10^−6 (0.988)	−0.0003 (0.657)	0.0002 (0.876)
$\hat{\beta}_{MON}$	−0.001 (0.003) ***	−0.001 (0.068) *	−0.0003 (0.199)	−2.4 × 10^−5 (0.968)	−0.002 (0.000) ***	−0.001 (0.008) ***	−0.001 (0.095) *	3.4 × 10^−5 (0.958)	−0.001 (0.009) ***	0.0002 (0.456)	0.001 (0.073) *
$\hat{\beta}_d$	−0.0004 (0.568)	−0.001 (0.266)	0.001 (0.153)	0.001 (0.354)	0.0003 (0.595)	0.001 (0.416)	0.0004 (0.659)	0.001 (0.481)	−0.001 (0.118)	0.001 (0.067) *	−0.001 (0.535)
$\hat{\beta}_{SAD}$	0.0003 (0.234)	0.001 (0.001) ***	−0.0002 (0.079) *	0.0001 (0.715)	0.0002 (0.214)	0.0004 (0.097) *	0.0001 (0.631)	0.0005 (0.062) **	0.001 (0.021) **	0.0004 (0.009) ***	4.4 × 10^−5 (0.850)
$\hat{\beta}_{FALL}$	0.0003 (0.513)	−0.001 (0.045) **	6.7 × 10^−5 (0.749)	−0.005 (0.362)	−0.0004 (0.114)	−0.001 (0.143)	−0.0003 (0.497)	−0.001 (0.119)	−0.0003 (0.469)	−0.001 (0.029) **	8.6 × 10^−5 (0.804)
$\hat{\rho}_{i-1}$	0.086 (0.000) ***	-	-	-	−0.744 (0.000) ***	0.047 (0.038) **	-	-	0.986 (0.000) ***	0.209 (0.000) ***	-
$\hat{\rho}_{i-2}$	0.021 (0.350)	-	-	-	-	-	-	-	-	-	-
$\hat{\rho}_{i-3}$	0.041 ** (0.069) ***	-	-	-	-	-	-	-	-	-	-
$\hat{\rho}_{i-4}$	0.044 (0.034) ***	-	-	-	-	-	-	-	-	-	-
$\hat{\varphi}_{i-1}$	-	-	-	-	0.780 (0.000) ***	-	-	−0.203 (0.000) ***	−0.974 (0.000) ***	-	-
GARCH equation											

[6] Since such markets exhibit behaviour which is not stable over time, maybe the regime switching methodology could be better to use in future work for more insightful information.

[7] However, the results for CROBEX are somewhat in line with Karadzic and Cerovic (2014). The long memory and predictability of CROBEX, SOFIX, and SAX is confirmed in Pece et al. (2013).

$\hat{\alpha}_{SAD}$	6.4×10^{-7} (0.115)	1.6×10^{-6} (0.574)	0.005 (0.154)	5.6×10^{-7} (0.155)	1.2×10^{-7} (0.461)	$2{-}2 \times 10^{-7}$ (0.693)	-9.8×10^{-7} (0.899)	**8.1×10^{-7} (0.000)** ***	**3×10^{-6} (0.011)** **	0.003 (0.492)	2.6×10^{-9} (0.991)
$\hat{\alpha}_{FALL}$	-6.5×10^{-8} (0.901)	-2.6×10^{-6} (0.545)	−0.0002 (0.970)	**-8.1×10^{-7} (0.085)** *	-1.2×10^{-7} (0.584)	6.2×10^{-7} (0.392)	5.9×10^{-6} (0.624)	**-1.7×10^{-6} (0.000)** ***	**-3.5×10^{-6} (0.006)** ***	−0.006 (0.226)	2.4×10^{-9} (0.993)
Model	GARCH	P-ARCH	EGARCH	GARCH	GARCH	GARCH	P-ARCH	GARCH	GARCH	EGARCH	GARCH

Note: *p*-values are given in parenthesis. *, ** and *** denote statistical significance on 10%, 5%, and 1%. Q(15) and $Q^2(15)$ refer to empirical Chi-squared values of testing autocorrelation and heteroskedasticity of residuals in the model up to lag 15. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30[8]. Detailed results on all GARCH models are given in tables in Appendix A. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects. Source: author's calculation.

5. Discussion

It can be concluded based upon the analysis carried out in this paper that 6 out of 11 observed markets exhibit *SAD* effects during the fall and winter period; 3 of those 6 additionally exhibit asymmetric effects (*FALL* variable). In that way, some additional anomalies do exist in the return series of those markets which are a result of time varying risk aversion of investors on the observed markets. The effects of seasonality on returns are similar across the observed markets, since they are close regarding the geographical latitude. Nevertheless, some other sources of differences of the non-existence of *SAD* effects on several markets surely exist.

The results for Croatia are similar to those in Škrinjarić et al. (2018), but here the results are extended to the GARCH specification of the model as well. Next, the results regarding Romania confirm previous findings of Murgea (2016), in which *SAD* effects were found in SOFIX returns for the period 2000–2014. However, the previous study did not observe asymmetric effects which were included here and found to be non-significant in return, but significant in risk series. The results for all of the markets were controlled for, as is typical in the related literature, with no significant relationship found between calendar effects and *SAD* effects, nor between conditional risks and *SAD* effects. Moreover, as it was seen in the literature review, the majority of markets observed in these study exhibit violations of the weak form of the Efficient Market Hypothesis, with some of them having long term memory of return series. Thus, the results in this study are in accordance with previous conclusions of those markets by using different methodology and answering questions regarding time varying risk aversion. Other markets observed in this study were not yet examined in such a fashion as they are here, to the knowledge of the author. That is why future work should check the validity of the results which are given here. However, since previous literature on EMH has provided evidence of similar behaviour of many CEE and SEE markets used in this study, there is some confidence in the validity of the obtained results.

Results in this research are useful for those investors who aim to obtain extra profits by doing some type of contrarian strategies compared to rest of the market. Such strategies could include selling part of the portfolio in the winter time due to returns being greater (positive *SAD* effects); and buying in fall time before the winter solstice (negative *FALL* effects), as well as buying on Mondays prior to the *SAD* effects on the majority of the examined markets (due to negative returns on Mondays). Since results indicate that *SAD* effects do not have prominent or significant influence on the volatility of the market, no specific investment strategy could be recommended at this stage. Further research could focus on different specifications of the risk and *SAD* relationship in order to get more insight into the possibilities of some hedging investment strategies. Moreover, the usage of rational asset pricing models should be taken with caution for those markets in which *SAD* effects

8 Additional tests on residuals were performed to test for normality: Lilliefors, Cramer von Mises, Watson and Anderson-Darling and all of the tests rejected the null hypothesis for every series. Detailed results are available upon request.

were found; especially those models which assume invariant investors' utility functions and preferences.

6. Conclusions

Theoretical and practical consequences of *SAD* effects on stock markets could be of great importance for those who deal with theoretical models in finance and investors in stock markets. The results in this research indicate that stock markets in Serbia, Hungary, Croatia, Slovakia, Romania, and Ukraine exhibit a *SAD* effect to some extent. This can be interpreted as investors in these markets face changing risk aversion over the year. Investors are affected by seasonal changes and thus their utility functions change over the year, resulting in different demand for higher return while bearing the same amount of risk. These results should be taken into consideration when applying and testing theoretical models on such stock markets, especially rational models which assume one form of human and investor behaviour. The results are in accordance with previous literature on the mentioned markets which has shown that these emerging markets exhibit predictive behaviour, they violate the weak from of the EMH, and long memory is present in return series. Secondly, some profitable trading strategies could be constructed in order to exploit such behaviour if it is found to be persistent in the future as well. Greater trading volume and interest in the examined markets could enable their faster development, especially when, even today, some of them are quite stagnant in terms of low trading volume. However, research should be careful when exploring profitable strategies, due to several existing studies which found that some forms of exploitation of existing anomalies can be profitable.

Shortfalls of the study are as follows. The whole time span was observed as a whole, due to observing the period from the beginning of 2010. An interesting further point to observe could be to include the period before the crisis and the last financial crisis in order to observe if the *SAD* effects change depending upon the state of the market. Moreover, future work should include theoretical contributions in terms of trying to explain the non-linear relationship of the *SAD* effects and return series if this type of relationship was found empirically. Future work should include development of trading strategies which could try to exploit predictive behaviour of investors and stock returns on specific markets. Finally, future work should include the analysis of the sources of (non)existence of *SAD* effects on specific markets as well. Thus, many possibilities exist to deepen the analysis and interest within this field of behavioural finance.

However, initial information was obtained for several markets for the first time in this study, both for return and risk variation over time. In that way, this research could be considered as a starting point for future work.

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Appendix A

Table A1. Different GARCH specifications for BELEX.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	0.0001 (0.569)	0.0001 (0.387)	0.0001 (0.581)	0.0002 (0.408)	0.0001 (0.545)
$\hat{\beta}_{JAN}$	−0.001 (0.283)	−0.001 (0.277)	−0.001 (0.284)	−0.001 (0.289)	−0.001 (0.304)
$\hat{\beta}_{MON}$	−0.001 (0.003) ***	−0.001 (0.008) *	−0.001 (0.003) ***	−0.001 (0.005) ***	0.0003 (0.270)
$\hat{\beta}_d$	−0.0004 (0.568)	−0.0004 (0.567)	−0.0004 (0.566)	−0.0004 (0.574)	−0.0004 (0.586)
$\hat{\beta}_{SAD}$	0.0003 (0.234)	0.0002 (0.384)	0.0003 (0.236)	0.0002 (0.339)	0.0003 (0.270)
$\hat{\beta}_{FALL}$	0.0003 (0.513)	0.0003 (0.507)	0.0003 (0.510)	0.0002 (0.519)	0.0003 (0.475)
$\hat{\rho}_{i-1}$	0.086 (0.000) ***	0.085 (0.000) ***	0.085 (0.000) ***	0.084 (0.000) ***	0.084 (0.000) ***
$\hat{\rho}_{i-2}$	0.021 (0.350)	0.016 (0.459)	0.021 (0.364)	0.018 (0.425)	0.020 (0.367)
$\hat{\rho}_{i-3}$	0.041 ** (0.069) ***	0.036 (0.105)	0.041 (0.069) *	0.038 (0.092) *	0.040 (0.075) *
$\hat{\rho}_{i-4}$	0.044 (0.034) ***	0.046 (0.024) **	0.043 (0.035) **	0.047 (0.023) **	0.044 (0.030) **
$\hat{\alpha}_0$	2.8×10^{-6} (0.000) ***	−0.812 (0.000) ***	2.8×10^{-6} (0.000) ***	0.0001 (0.465)	-
$\hat{\alpha}_1$	0.130 (0.000) ***	0.277 (0.000) ***	0.128 (0.000) ***	0.148 (0.000) ***	4.925 (0.000) ***
$\hat{\beta}_1$	0.816 (0.000) ***	0.940 (0.000) ***	0.816 (0.000) ***	0.829 (0.000) ***	0.721 (0.000) ***
$\hat{\gamma}$	-	−0.002 (0.931)	-	-	-
$\hat{\pi}$	-	-	0.004 (0.903)	-	-
$\hat{\theta}$	-	-	-	−0.005 (0.943)	-
$\hat{\tau}$	-	-	-	1.247 (0.000) ***	-
$\hat{\varpi}$	-	-	-	-	4.6×10^{-5} (0.001) ***
$\hat{\xi}$	-	-	-	-	0.985 (0.000) ***
$\hat{\psi}$	-	-	-	-	0.042 (0.034) **
$\hat{\alpha}_{SAD}$	6.4×10^{-7} (0.115)	0.009 (0.233)	6.4×10^{-7} (0.116)	1.4×10^{-5} (0.450)	3.4×10^{-8} (0.226)
$\hat{\alpha}_{FALL}$	-6.5×10^{-8} (0.901)	0.002 (0.790)	-6.6×10^{-8} (0.903)	6.9×10^{-8} (0.996)	**0.721 (0.000) *****
t-dist DoF	4.977 (0.000) ***	5.036 (0.000) ***	4.971 (0.000) ***	4.995 (0.000) ***	4.925 (0.000) ***
Log L	7544.519	7547.885	7544.527	7547.069	7548.756

Q (15)	18.804 (0.065) *	18.047 (0.080) *	18.754 (0.066) *	19.298 (0.056) *	17.915 (0.084) *
Q^2 (15)	12.566 (0.323)	20.538 (0.038) **	12.418 (0.333)	24.474 (0.011) **	11.703 (0.386)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. Q (15) and Q^2 (15) refer to empirical Chi-squared values of testing autocorrelation and heteroskedasticity of residuals in the model up to lag 15. The condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met; whilst the remained heteroskedasticity in models E-GARCH and P-ARCH excluded them from further analysis. Between GARCH and T-GARCH models, the original GARCH was chosen due to the parameter $\hat{\pi}$ not being significant (meaning no difference between good and bad news on the market on the variance). Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A2. Different GARCH specifications for BETI.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	0.0004 (0.061) *	0.0004 (0.086) *	0.0004 (0.119)	0.0004 (0.116)	0.0004 (0.052) *
$\hat{\beta}_{JAN}$	−0.0016 (0.079) *	−0.0013 (0.147)	−0.0015 (0.098) *	−0.001 (0.107)	−0.001 (0.132)
$\hat{\beta}_{MON}$	−0.001 (0.085) *	−0.001 (0.059) *	−0.001 (0.068) *	−0.001 (0.068) *	−0.001 (0.115)
$\hat{\beta}_d$	−0.001 (0.372)	−0.001 (0.189)	−0.001 (0.290)	−0.001 (0.266)	−0.001 (0.328)
$\hat{\beta}_{SAD}$	**0.001 (0.001) *** **	**0.001 (0.001) *** **	**0.001 (0.001) *** **	**0.001 (0.001) *** **	**0.001 (0.002) *** **
$\hat{\beta}_{FALL}$	**−0.001 (0.030) ** **	**−0.001 (0.064) * **	**−0.001 (0.040) ** **	**−0.001 (0.045) ** **	**−0.001 (0.045) ** **
$\hat{\alpha}_0$	4.1×10^{-6} (0.000) ***	−0.652 (0.000) ***	4.3×10^{-6} (0.000) ***	1.4×10^{-5} (0.554)	-
$\hat{\alpha}_1$	0.127 (0.000) ***	0.250 (0.000) ***	0.085 (0.001) ***	0.130 (0.000) ***	4.914 (0.000) ***
$\hat{\beta}_1$	0.829 (0.000) ***	0.951 (0.000) ***	0.824 (0.000) ***	0.830 (0.000) ***	0.798 (0.000) ***
$\hat{\gamma}$	-	−0.055 (0.003) ***	-	-	-
$\hat{\pi}$	-	-	0.085 (0.005) ***	-	-
$\hat{\theta}$	-	-	-	0.193 (0.012) **	-
$\hat{\tau}$	-	-	-	1.745 (0.000)***	-
$\hat{\varpi}$	-	-	-	-	1×10^{-5} (0.822)
$\hat{\xi}$	-	-	-	-	0.997 (0.000) ***
$\hat{\psi}$	-	-	-	-	2.5×10^{-7} (0.361)
$\hat{\alpha}_{SAD}$	4.2×10^{-7} (0.394)	0.006 (0.350)	5.4×10^{-7} (0.292)	1.6×10^{-6} (0.574)	-1.6×10^{-7} (0.628)
$\hat{\alpha}_{FALL}$	-7×10^{-7} (0.218)	−0.013 (0.137)	-8.4×10^{-7} (0.149)	-2.6×10^{-6} (0.545)	**0.798 (0.000) *** **
t-dist DoF	5.058 (0.000) ***	5.115 (0.000) ***	5.225 (0.000) ***	5.233 (0.000) ***	4.914 (0.000) ***

Log L	7024.627	7022.775	7028.692	7029.027	7033.081
Q (15)	20.158 (0.166)	19.609 (0.187)	20.017 (0.171)	19.814 (0.179)	18.561 (0.234)
Q^2 (15)	19.948 (0.174)	21.394 (0.125)	21.479 (0.122)	21.577 (0.119)	15.425 (0.421)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. The condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met. P-ARCH was chosen as having greatest Log L. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A3. Different GARCH specifications for BIRS.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	−2.5 × 10^{-5} (0.833)	−4.4 × 10^{-5} (0.971)	−1.5 × 10^{-5} (0.971)	−1.7 × 10^{-5} (0.820)	−1.5 × 10^{-5} (0.903)
$\hat{\beta}_{JAN}$	0.001 (0.132)	0.001 (0.097) *	0.001 (0.229)	0.001 (0.016) **	0.001 (0.129)
$\hat{\beta}_{MON}$	−0.0003 (0.155)	−0.0003 (0.199)	−0.0004 (0.093) *	−0.0001 (0.396)	−0.0003 (0.140)
$\hat{\beta}_d$	0.001 (0.083) *	0.001 (0.153)	0.001 (0.098) *	0.0004 (0.158)	0.001 (0.093) *
$\hat{\beta}_{SAD}$	−0.0002 (0.105)	−0.0002 (0.079) *	−0.0002 (0.119)	**−0.0003 (0.028) ****	**−0.0002 (0.092) ***
$\hat{\beta}_{FALL}$	4.4 × 10^{-6} (0.984)	6.7 × 10^{-5} (0.749)	−7.5 × 10^{-6} (0.975)	0.0001 (0.425)	7.9 × 10^{-6} (0.971)
$\hat{\alpha}_0$	5.7 × 10^{-6} (0.467)	−0.208 (0.000) ***	4.6 × 10^{-7} (0.012) **	0.003 (0.168)	-
$\hat{\alpha}_1$	0.232 (0.436)	0.214 (0.003) ***	0.041 (0.000) ***	0.069 (0.001) ***	2.339 (0.000) ***
$\hat{\beta}_1$	0.953 (0.000) ***	0.984 (0.000) ***	0.957 (0.000) ***	0.950 (0.000) ***	−0.502 (0.018) **
$\hat{\gamma}$	-	0.051 (0.095) *	-	-	-
$\hat{\pi}$	-	-	−0.030 (0.005) ***	-	-
$\hat{\theta}$	-	-	-	−0.130 (0.000) ***	-
$\hat{\tau}$	-	-	-	0.419 (0.001) ***	-
$\hat{\varpi}$	-	-	-	-	0.018 (0.369)
$\hat{\xi}$	-	-	-	-	0.9999 (0.000) ***
$\hat{\psi}$	-	-	-	-	0.110 (0.011) **
$\hat{\alpha}_{SAD}$	2.7 × 10^{-6} (0.489)	0.005 (0.154)	1.1 × 10^{-7} (0.325)	0.0001 (0.421)	−2.6 × 10^{-8} (0.937)
$\hat{\alpha}_{FALL}$	−9.4 × 10^{-7} (0.645)	−0.0002 (0.970)	9.5 × 10^{-8} (0.525)	4.8 × 10^{-5} (0.784)	**−0.502 (0.018) ****
t-dist DoF	2.054 (0.000) ***	2.116 (0.000) ***	1.699 (0.000) ***	2.095 (0.000) ***	2.339 (0.000) ***
Log L	7913.856	7933.976	7889.419	7945.727	7913.247

Q (15)	10.948 (0.756)	9.891 (0.827)	11.807 (0.694)	10.514 (0.786)	12.312 (0.655)
Q^2 (15)	19.845 (0.178)	22.380 (0.098) *	23.514 (0.074) *	35.124 (0.002) ***	19.057 (0.211)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. Summary of parameters in GARCH model do not satisfy the restriction $\hat{\alpha}_1 + \hat{\beta}_1 < 1$; condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met as well; heteroskedasticity is still present in P-ARCH model and the Log L was greatest for EGARCH model so this one was chosen as best one. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A4. Different GARCH specifications for BUX.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	0.0004 (0.278)	5.4×10^{-5} (0.867)	0.0001 (0.734)	7.8×10^{-5} (0.808)	0.0003 (0.292)
$\hat{\beta}_{JAN}$	0.001 (0.539)	0.001 (0.338)	0.001 (0.383)	0.001 (0.370)	0.001 (0.530)
$\hat{\beta}_{MON}$	-2.4×10^{-5} (0.968)	4.6×10^{-5} (0.937)	2.7×10^{-5} (0.964)	3.3×10^{-5} (0.957)	-3.7×10^{-5} (0.951)
$\hat{\beta}_d$	0.001 (0.354)	0.001 (0.265)	0.001 (0.335)	0.001 (0.321)	0.001 (0.368)
$\hat{\beta}_{SAD}$	0.0001 (0.715)	7.5×10^{-5} (0.827)	0.0001 (0.715)	9.8×10^{-5} (0.780)	0.0001 (0.719)
$\hat{\beta}_{FALL}$	−0.005 (0.362)	−0.0004 (0.359)	−0.0005 (0.333)	−0.0005 (0.360)	−0.0005 (0.368)
$\hat{\alpha}_0$	2.5×10^{-6} (0.012) **	−0.234 (0.000) ***	2.4×10^{-6} (0.004) ***	4.5×10^{-5} (0.466)	-
$\hat{\alpha}_1$	0.061 (0.000) ***	0.095 (0.000) ***	0.006 (0.563)	0.046 (0.002) ***	7.838 (0.000) ***
$\hat{\beta}_1$	0.922 (0.000) ***	0.982 (0.000) ***	0.931 (0.000) ***	0.941 (0.000) ***	−0.828 (0.019) **
$\hat{\gamma}$	-	−0.080 (0.000) ***	-	-	-
$\hat{\pi}$	-	-	0.092 (0.000) ***	-	-
$\hat{\theta}$	-	-	-	0.800 (0.003) ***	-
$\hat{\tau}$	-	-	-	1.328 (0.000) ***	-
$\hat{\varpi}$	-	-	-	-	0.0001 (0.000) ***
$\hat{\xi}$	-	-	-	-	0.983 (0.000) ***
$\hat{\psi}$	-	-	-	-	0.058 (0.000) ***
$\hat{\alpha}_{SAD}$	5.6×10^{-7} (0.155)	**0.006 (0.031) ****	4.5×10^{-7} (0.208)	8.1×10^{-6} (0.457)	**-8×10^{-7} (0.085) ***
$\hat{\alpha}_{FALL}$	**-8.1×10^{-7} (0.085) ***	**−0.009 (0.026) ****	-6.8×10^{-7} (0.115)	-1.1×10^{-5} (0.441)	**−0.828 (0.019) ****
t-dist DoF	7.785 (0.000) ***	8.625 (0.000) ***	8.674 (0.000) ***	8.748 (0.000) ***	7.838 (0.000) ***
Log L	6315.697	6333.369	6331.414	6334.121	6316.054

Q (15)	11.031 (0.750)	11.026 (0.751)	10.445 (0.791)	11.131 (0.743)	10.873 (0.762)
Q^2 (15)	16.997 (0.319)	31.867 (0.007) ***	24.407 (0.059) *	30.512 (0.010) **	15.196 (0.437)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. Condition in C-GARCH 0 < $\hat{\alpha}_1 + \hat{\beta}_1$ < $\hat{\xi}$ < 1 is not met; heteroskedasticity is still present in EGARCH and P-ARCH models. Although the Log L is greater for the T-GARCH model, no heteroskedasticity is left in the GARCH model. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A5. Different GARCH specifications for CROBEX[9].

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	0.0004 (0.026) **	0.0003 (0.093) *	0.0003 (0.050) *	0.0003 (0.042) **	0.0004 (0.030) **
$\hat{\beta}_{JAN}$	0.0003 (0.699)	6.6×10^{-5} (0.918)	0.0002 (0.817)	0.0002 (0.786)	0.0004 (0.568)
$\hat{\beta}_{MON}$	−0.002 (0.000) ***	−0.002 (0.000) ***	−0.002 (0.000) ***	−0.002 (0.000) ***	−0.002 (0.000) ***
$\hat{\beta}_d$	0.0003 (0.595)	0.0003 (0.649)	0.0004 (0.507)	0.0003 (0.549)	0.0003 (0.573)
$\hat{\beta}_{SAD}$	0.0002 (0.214)	0.0002 (0.185)	0.0002 (0.176)	0.0003 (0.142)	0.0002 (0.189)
$\hat{\beta}_{FALL}$	−0.0004 (0.114)	−0.0004 (0.119)	**−0.0005 (0.082) ***	**−0.0004 (0.086) ***	−0.0005 (0.101)
$\hat{\rho}_{i-1}$	−0.744 (0.000) ***	0.915 (0.000) ***	−0.736 (0.000) ***	−0.748 (0.000) ***	−0.764 (0.000) ***
$\hat{\varphi}_{i-1}$	0.780 (0.000) ***	−0.897 (0.000) ***	0.774 (0.000) ***	0.782 (0.000) ***	0.797 (0.000) ***
$\hat{\alpha}_0$	1.6×10^{-6} (0.000) ***	−0.477 (0.000) ***	1.3×10^{-6} (0.000) ***	0.0001 (0.491)	-
$\hat{\alpha}_1$	0.099 (0.000) ***	0.177 (0.000) ***	0.053 (0.001) ***	0.099 (0.000) ***	5.750 (0.000) ***
$\hat{\beta}_1$	0.860 (0.000) ***	0.967 (0.000) ***	0.882 (0.000) ***	0.887 (0.000) ***	0.810 (0.000) ***
$\hat{\gamma}$	-	−0.040 (0.011) **	-	-	-
$\hat{\pi}$	-	-	0.058 (0.008) ***	-	-
$\hat{\theta}$	-	-	-	0.203 (0.020) **	-

[9] One referee pointed out that the values of the ARMA parameters had great magnitude. That is why the following ARMA(p,q) models have been observed for the CROBEX return: AR(2), MA(2), ARMA(1,1), ARMA(2,2), ARMA(3,3), ARMA(2,1), and ARMA(1,2) in order to see if the values of parameters change significantly. The results (details are available upon request) indicated that when the values of parameters were smaller they were not significant at all. ARMA(1,1) model resulted with no problems of autocorrelation and heteroskedasticity of residuals and thus this model was left in the rest of the analysis with GARCH specifications. The following papers confirm that the Croatian stock market is not efficient in terms of the Efficient Market Hypothesis: Heininen and Puttonen (2008), Barbić (2010), Šego and Škrinjarić (2012). However, these inefficiencies were found to be not much exploitable (in (Škrinjarić 2013) and (Radovanov and Marcikić 2017)).

$\hat{\tau}$	-	-	-	1.137 (0.000) ***	-
$\hat{\varpi}$	-	-	-	-	1.1×10^{-5} (0.693)
$\hat{\xi}$	-	-	-	-	0.998 (0.000) ***
$\hat{\psi}$	-	-	-	-	−0.001 (0.762)
$\hat{\alpha}_{SAD}$	8.7×10^{-8} (0.645)	0.003 (0.522)	1.2×10^{-7} (0.461)	6.2×10^{-6} (0.593)	3.4×10^{-8} (0787)
$\hat{\alpha}_{FALL}$	-9×10^{-8} (0.706)	−0.002 (0.767)	-1.2×10^{-7} (0.584)	-5.4×10^{-6} (0.675)	**0.810 (0.000) *** **
t-dist DoF	5.768 (0.000) ***	5.922 (0.000) ***	5.885 (0.000) ***	5.911 (0.000) ***	5.750 (0.000) ***
Log L	7680.070	7685.541	7683.260	7687.072	7690.087
Q (15)	20.933 (0.074) *	18.059 (0.155)	23.007 (0.042) **	24.251 (0.029) **	26.644 (0.026) **
Q^2 (15)	4.714 (0.981)	3.296 (0.997)	3.565 (0.995)	3.174 (0.997)	4.210 (0.989)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. Condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met. Autocorrelation of residuals is present on 5% in models T-GARCH and P-ARCH. Finally, model GARCH is chosen due to having similar parameters of ARMA terms compared to other models although having lover Log L. Residuals from the GARCH models were extracted and Engle and Ng (1993) sign bias and negative size bias tests were performed to see if asymmetric effects of news shocks should be included as in EGARCH model. Results rejected significance of sign and negative sizes. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A6. Different GARCH specifications for SBITOP.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	7.3×10^{-5} (0.754)	-1.5×10^{-5} (0.949)	2.4×10^{-5} (0.919)	2×10^{-5} (0.932)	8.2×10^{-5} (0.726)
$\hat{\beta}_{JAN}$	−0.0004 (0.631)	−0.0004 (0.622)	−0.0004 (0.623)	−0.0004 (0.619)	−0.0004 (0.635)
$\hat{\beta}_{MON}$	−0.001 (0.008) ***	−0.001 (0.009) ***	−0.001 (0.008) ***	−0.001 (0.008) ***	−0.001 (0.007) ***
$\hat{\beta}_d$	0.001 (0.416)	0.001 (0.489)	0.001 (0.437)	0.001 (0.443)	0.001 (0.397)
$\hat{\beta}_{SAD}$	**0.0004 (0.097) ***	**0.0004 (0.095) ***	**0.0004 (0.089) ***	**0.0004 (0.089) ***	0.0004 (0.104)
$\hat{\beta}_{FALL}$	−0.001 (0.143)	−0.001 (0.147)	−0.001 (0.146)	−0.001 (0.147)	−0.001 (0.123)
$\hat{\rho}_{i-1}$	0.047 (0.038) **	0.043 (0.049) **	0.047 (0.041) **	0.046 (0.044) **	0.056 (0.017) **
$\hat{\alpha}_0$	6.5×10^{-6} (0.000) ***	−0.879 (0.000) ***	6.3×10^{-5} (0.000) ***	1.4×10^{-5} (0.647)	-
$\hat{\alpha}_1$	0.144 (0.000) ***	0.250 (0.000) ***	0.115 (0.000) ***	0.140 (0.000) ***	5.846 (0.000) ***
$\hat{\beta}_1$	0.775 (0.000) ***	0.928 (0.000) ***	0.781 (0.000) ***	0.791 (0.000) ***	0.622 (0.000) ***

$\hat{\gamma}$	-	−0.032 (0.120)	-	-	-
$\hat{\pi}$	-	-	0.050 (0.165)	-	-
$\hat{\theta}$	-	-	-	0.094 (0.180)	-
$\hat{\tau}$	-	-	-	1.830 (0.000) ***	-
$\hat{\varpi}$	-	-	-	-	6.6 × 10^{-5} (0.009) ***
$\hat{\xi}$	-	-	-	-	0.995 (0.000) ***
$\hat{\psi}$	-	-	-	-	0.144 (0.000) ***
$\hat{\alpha}_{SAD}$	2.2 × 10^{-7} (0.693)	−0.003 (0.718)	−1.4 × 10^{-7} (0.807)	−3.2 × 10^{-7} (0.815)	7.3 × 10^{-9} (0.972)
$\hat{\alpha}_{FALL}$	6.2 × 10^{-7} (0.392)	0.007 (0.461)	5.3 × 10^{-7} (0.457)	1.1 × 10^{-6} (0.672)	**0.622 (0.000)** ***
t-dist DoF	5.408 (0.000) ***	5.388 (0.000) ***	5.411 (0.000) ***	5.420 (0.000) ***	5.846 (0.000) ***
Log L	7004.063	7002.518	7005.083	7005.176	7013.630
Q (15)	11.017 (0.685)	11.336 (0.659)	11.302 (0.662)	11.370 (0.657)	9.909 (0.769)
Q² (15)	10.250 (0.744)	10.419 (0.731)	10.267 (0.742)	10.319 (0.739)	7.604 (0.909)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. Condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met. Since parameters which are specific in models E-GARCH, T-GARCH and P-ARCH (measuring asymmetry in risk behaviour) are not significant, model GARCH was chosen as best one. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A7. Different GARCH specifications for PX.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	0.001 (0.021) **	0.0005 (0.113)	0.0005 (0.095) *	0.0005 (0.112)	0.001 (0.024) **
$\hat{\beta}_{JAN}$	−0.002 (0.050) *	−0.001 (0.245)	−0.001 (0.207)	−0.001 (0.274)	−0.002 (0.052) *
$\hat{\beta}_{MON}$	−0.001 (0.162)	−0.001 (0.077) *	−0.001 (0.133)	−0.001 (0.095) *	−0.001 (0.172)
$\hat{\beta}_d$	−2.6 × 10^{-5} (0.979)	0.0004 (0.684)	0.0004 (0.676)	0.0004 (0.659)	−2.2 × 10^{-5} (0.982)
$\hat{\beta}_{SAD}$	0.0003 (0.341)	0.0002 (0.560)	0.0002 (0.509)	0.0001 (0.631)	0.0003 (0.367)
$\hat{\beta}_{FALL}$	−0.0003 (0.550)	−0.0003 (0.488)	−0.0004 (0.415)	−0.0003 (0.497)	−0.0003 (0.557)
$\hat{\alpha}_0$	4.6 × 10^{-6} (0.002) ***	−0.518 (0.000) ***	5.9 × 10^{-6} (0.000) ***	0.0002 (0.469)	-
$\hat{\alpha}_1$	0.080 (0.000) ***	0.153 (0.000) ***	0.009 (0.581)	0.077 (0.000) ***	7.062 (0.000) ***
$\hat{\beta}_1$	0.884 (0.000) ***	0.956 (0.000) ***	0.877 (0.000) ***	0.886 (0.000) ***	0.438 (0.243)

$\hat{\gamma}$	-	−0.094 (0.000) ***	-	-	-
$\hat{\pi}$	-	-	0.133 (0.000) ***	-	-
$\hat{\theta}$	-	-	-	0.669 (0.000) ***	-
$\hat{\tau}$	-	-	-	1.270 (0.000) ***	-
$\hat{\varpi}$	-	-	-	-	0.0001 (0.000) ***
$\hat{\xi}$	-	-	-	-	0.978 (0.000) ***
$\hat{\psi}$	-	-	-	-	0.056 (0.000) ***
$\hat{\alpha}_{SAD}$	-5×10^{-8} (0.905)	−0.002 (0.646)	-2.6×10^{-8} (0.953)	-9.8×10^{-7} (0.899)	3.7×10^{-7} (0.435)
$\hat{\alpha}_{FALL}$	3.3×10^{-7} (0.581)	0.0003 (0.546)	5.4×10^{-7} (0.393)	5.9×10^{-6} (0.624)	0.438 (0.243)
t-dist DoF	6.999 (0.000)	7.310 (0.000) ***	7.277 (0.000) ***	7.395 (0.000) ***	7.062 (0.000) ***
Log L	6456.816	6469.887	6471.077	6473.404	6458.436
Q (15)	20.222 (0.164)	20.033 (0.171)	20.811 (0.143)	20.145 (0.166)	20.347 (0.159)
Q^2 (15)	7.584 (0.939)	9.510 (0.849)	8.668 (0.894)	9.506 (0.850)	5.071 (0.992)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. Condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A8. Different GARCH specifications for SAX.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	-8.7×10^{-5} (0.774)	-8.2×10^{-5} (0.757)	-3.1×10^{-5} (0.900)	0.0002 (0.200)	-3.4×10^{-5} (0.898)
$\hat{\beta}_{JAN}$	−0.001 (0.262)	−0.002 (0.069) *	−0.001 (0.141)	−0.001 (0.304)	−0.001 (0.107)
$\hat{\beta}_{MON}$	3.4×10^{-5} (0.958)	-2.6×10^{-5} (0.969)	4.8×10^{-5} (0.942)	0.0002 (0.543)	−0.0002 (0.861)
$\hat{\beta}_d$	0.001 (0.481)	0.001 (0.279)	0.0004 (0.535)	5.4×10^{-5} (0.928)	0.001 (0.289)
$\hat{\beta}_{SAD}$	**0.0005 (0.062) ****	**0.001 (0.005) *****	**0.0004 (0.057) ***	0.0001 (0.469)	**0.001 (0.014) ****
$\hat{\beta}_{FALL}$	−0.001 (0.119)	**−0.001 (0.018) ****	−0.001 (0.138)	−0.0001 (0.627)	**−0.001 (0.035) ****
$\hat{\rho}_{i-1}$	-	0.662 (0.000) ***	0.650 (0.000) ***	0.840 (0.000) ***	0.641 (0.000) ***
$\hat{\rho}_{i-2}$	-	0.107 (0.002) ***	0.113 (0.000) ***	-	0.112 (0.002) ***
$\hat{\varphi}_{i-1}$	−0.203 (0.000) ***	−0.847 (0.000) ***	−0.854 (0.000) ***	−0.954 (0.000) ***	−0.842 (0.000) ***
$\hat{\varphi}_{i-2}$	-	-	-	0.078 (0.001) ***	-

$\hat{\alpha}_0$	4.6×10^{-6} (0.000) ***	−4.170 (0.000) ***	2.9×10^{-6} (0.000) ***	0.007 (0.306)	-
$\hat{\alpha}_1$	0.025 (0.000) ***	0.170 (0.000) ***	0.037 (0.000) ***	0.209 (0.052) *	−0.791 (0.065) *
$\hat{\beta}_1$	0.937 (0.000) ***	0.549 (0.000) ***	0.954 (0.000) ***	0.836 (0.000) ***	0.744 (0.103)
$\hat{\gamma}$	-	−0.041 (0.046) **	-	-	-
$\hat{\pi}$	-	-	−0.024 (0.000) ***	-	-
$\hat{\theta}$	-	-	-	0.111 (0.498)	-
$\hat{\tau}$	-	-	-	0.703 (0.001) ***	-
$\hat{\varpi}$	-	-	-	-	0.0001 (0.000) ***
$\hat{\xi}$	-	-	-	-	0.093 (0.097) *
$\hat{\psi}$	-	-	-	-	0.826 (0.053) *
$\hat{\alpha}_{SAD}$	**8.1×10^{-7} (0.000) *** **	−0.009 (0.316)	**5×10^{-7} (0.000) *** **	0.0002 (0.450)	-1.7×10^{-6} (0.490)
$\hat{\alpha}_{FALL}$	**-1.7×10^{-6} (0.000) *** **	**−0.037 (0.007) *** **	**-1.2×10^{-6} (0.000) *** **	6.8×10^{-5} (0.818)	0.744 (0.103)
t-dist DoF	2 (0.000) ***	2.061 (0.000) ***	2 (0.000) ***	2.080 (0.000) ***	2.141 (0.000) ***
Log L	6185.770	6169.446	6187.473	6499.096	6181.706
Q (15)	22.417 (0.070) *	18.579 (0.099) *	16.023 (0.190)	25.377 (0.013) **	18.828 (0.093) *
Q^2 (15)	26.511 (0.022) **	36.195 (0.000) ***	38.881 (0.000) ***	26.704 (0.009) ***	53.566 (0.000) ***

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. EGARCH, T-GARCH and C-GARCH were estimated with assumptions of normal, *t*-distribution and GED, however, the remaining heteroskedasticity was still present in all three models. Condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A9. Different GARCH specifications for SOFIX.

Estimated Values/Diagnostics	**GARCH**	**E-GARCH**	**T-GARCH**	**P-ARCH**	**C-GARCH**
$\hat{\beta}_0$	0.0003 (0.358)	0.0002 (0.503)	0.0002 (0.468)	0.0002 (0.461)	0.0002 (0.368)
$\hat{\beta}_{JAN}$	1.4×10^{-6} (0.988)	2.1×10^{-5} (0.981)	4.3×10^{-5} (0.964)	5.6×10^{-5} (0.953)	1.6×10^{-5} (0.987)
$\hat{\beta}_{MON}$	−0.001 (0.009) ***	−0.001 (0.012) **	−0.001 (0.009) ***	−0.001 (0.009) ***	−0.001 (0.009) ***
$\hat{\beta}_d$	−0.001 (0.118)	−0.001 (0.128)	−0.001 (0.121)	−0.001 (0.122)	−0.001 (0.128)
$\hat{\beta}_{SAD}$	**0.001 (0.021) ** **	**0.001 (0.013) ** **	**0.001 (0.022) ** **	**0.001 (0.024) ** **	**0.001 (0.020) ** **
$\hat{\beta}_{FALL}$	−0.0003 (0.469)	−0.0004 (0.359)	−0.0003 (0.478)	−0.0003 (0.488)	−0.0003 (0.451)

$\hat{\rho}_{i-1}$	0.986 (0.000) ***	0.984 (0.000) ***	0.986 (0.000) ***	0.986 (0.000) ***	0.986 (0.000) ***
$\hat{\varphi}_{i-1}$	−0.974 (0.000) ***	−0.972 (0.000) ***	−0.974 (0.000) ***	−0.974 (0.000) ***	−0.974 (0.000) ***
$\hat{\alpha}_0$	8.4×10^{-6} (0.000) ***	−1.686 (0.000) ***	8.6×10^{-6} (0.000) ***	3.6×10^{-6} (0.659)	-
$\hat{\alpha}_1$	0.222 (0.000) ***	0.384 (0.000) ***	0.198 (0.000) ***	0.220 (0.000) ***	4.993 (0.000) ***
$\hat{\beta}_1$	0.645 (0.011) **	0.858 (0.000) ***	0.636 (0.000) ***	0.624 (0.000) ***	0.447 (0.777)
$\hat{\gamma}$	-	−0.022 (0.423)	-	-	-
$\hat{\pi}$	-	-	0.053 (0.325)	-	-
$\hat{\theta}$	-	-	-	0.057 (0.331)	-
$\hat{\tau}$	-	-	-	2.182 (0.000) ***	-
$\hat{\varpi}$	-	-	-	-	6.3×10^{-5} (0.000) ***
$\hat{\xi}$	-	-	-	-	0.875 (0.000) ***
$\hat{\psi}$	-	-	-	-	0.206 (0.013) **
$\hat{\alpha}_{SAD}$	**3×10^{-6} (0.011) ****	**0.038 (0.008) *****	**3.2×10^{-6} (0.008) *****	1.5×10^{-6} (0.625)	**-3.3×10^{-6} (0.013) ****
$\hat{\alpha}_{FALL}$	**-3.5×10^{-6} (0.006) *****	**−0.040 (0.019) ****	**-3.7×10^{-6} (0.005) *****	-1.7×10^{-6} (0.625)	0.447 (0.777)
t-dist DoF	5 (0.000) ***	4.806 (0.000) ***	5.024 (0.000) ***	5.037 (0.000) ***	4.993 (0.000) ***
Log L	7234.218	7229.291	7234.696	7234.782	7234.308
Q (15)	16.737 (0.212)	15.756 (0.263)	11.648 (0.474)	17.110 (0.194)	16.520 (0.222)
Q^2 (15)	9.869 (0.705)	8.628 (0.800)	9.435 (0.739)	9.682 (0.720)	10.480 (0.654)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. Condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met. Since several parameters were not significant in EGARCH, T-GARCH and P-ARCH, the GARCH model was chosen as best one. However, it can be seen that the *SAD* effects are very similar in all of the observed models[10]. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

[10] Moreover, the great values of ARMA parameters in all models have been double checked. Other literature is found which obtained similar parameters: Marinela (2014). Moreover, the long memory in Bulgarian returns is found to be rising over time, as found in Necula and Radu (2012).

Table A10. Different GARCH specifications for PFTS.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	−0.0002 (0.383)	−0.0003 (0.109)	−0.0002 (0.232)	−0.0003 (0.135)	-5.2×10^{-6} (0.842)
$\hat{\beta}_{JAN}$	−0.0002 (0.707)	−0.0003 (0.657)	−0.0003 (0.676)	0.0002 (0.807)	−0.0003 (0.710)
$\hat{\beta}_{MON}$	0.0002 (0.533)	0.0002 (0.456)	0.0002 (0.553)	0.0002 (0.429)	0.0003 (0.269)
$\hat{\beta}_d$	0.001 (0.088) *	0.001 (0.067) *	0.001 (0.073) *	0.001 (0.079) *	0.001 (0.535)
$\hat{\beta}_{SAD}$	**0.0004 (0.016) ****	**0.0004 (0.009) *****	**0.0004 (0.010) ****	**0.0003 (0.026) ****	**0.0003 (0.077) ***
$\hat{\beta}_{FALL}$	**−0.001 (0.032) ****	**−0.001 (0.029) ****	**−0.001 (0.027) ****	**−0.0004 (0.052) ***	−0.0004 (0.297)
$\hat{\rho}_{i-1}$	0.231 (0.000) ***	0.209 (0.000) ***	0.222 (0.000) ***	0.211 (0.000) ***	0.252 (0.000) ***
$\hat{\alpha}_0$	1.5×10^{-6} (0.011) **	−0.288 (0.000) ***	1.4×10^{-6} (0.011) **	0.0001 (0.144)	-
$\hat{\alpha}_1$	0.381 (0.000) ***	0.225 (0.000) ***	0.248 (0.000) ***	0.209 (0.000) ***	18.703 (0.000) ***
$\hat{\beta}_1$	0.787 (0.000) ***	0.983 (0.000) ***	0.804 (0.000) ***	0.856 (0.000) ***	0.187 (0.074) *
$\hat{\gamma}$	-	−0.101 (0.000) ***	-	-	-
$\hat{\pi}$	-	-	0.199 (0.008) ***	-	-
$\hat{\theta}$	-	-	-	0.135 (0.052) *	-
$\hat{\tau}$	-	-	-	0.753 (0.000) ***	-
$\hat{\varpi}$	-	-	-	-	0.002 (0.000) ***
$\hat{\xi}$	-	-	-	-	0.9997 (0.000) ***
$\hat{\psi}$	-	-	-	-	0.153 (0.000) ***
$\hat{\alpha}_{SAD}$	-1.3×10^{-7} (0.653)	0.003 (0.492)	-8.1×10^{-8} (0.753)	2.4×10^{-7} (0.997)	**-1.7×10^{-7} (0.032) ****
$\hat{\alpha}_{FALL}$	-1.8×10^{-7} (0.454)	−0.006 (0.226)	-1.8×10^{-7} (0.447)	-4.3×10^{-5} (0.553)	**0.188 (0.074) ***
t-dist DoF	2.784 (0.000) ***	2.790 (0.000) ***	2.775 (0.000) ***	2.843 (0.000) ***	18.703 (0.000) ***
Log L	6570.055	6614.415	6617.720	6641.325	6469.517
Q (15)	8.832 (0.842)	11.799 (0.622)	8.056 (0.886)	8.587 (0.857)	8.857 (0.840)
Q^2 (15)	0.032 (1.000)	0.033 (1.000)	0.029 (1.000)	0.030 (1.000)	0.035 (1.000)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5%, and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. The sum of the parameters in GARCH model exceeds unit value. Condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

Table A11. Different GARCH specifications for WIG.

Estimated Values/Diagnostics	GARCH	E-GARCH	T-GARCH	P-ARCH	C-GARCH
$\hat{\beta}_0$	0.0003 (0.291)	0.0001 (0.681)	0.0001 (0.677)	9.8 × 10^{-5} (0.704)	0.0003 (0.289)
$\hat{\beta}_{JAN}$	0.0002 (0.876)	0.0001 (0.915)	4.1 × 10^{-5} (0.967)	2.7 × 10^{-5} (0.978)	0.0002 (0.874)
$\hat{\beta}_{MON}$	0.001 (0.073) *	0.001 (0.043) **	0.001 (0.076) *	0.001 (0.064) *	0.001 (0.074) *
$\hat{\beta}_d$	−0.001 (0.535)	−0.001 (0.265)	−0.001 (0.401)	−0.001 (0.344)	−0.001 (0.541)
$\hat{\beta}_{SAD}$	4.4 × 10^{-5} (0.850)	7.2 × 10^{-5} (0.745)	0.0001 (0.655)	9.4 × 10^{-5} (0.674)	4.1 × 10^{-5} (0.860)
$\hat{\beta}_{FALL}$	8.6 × 10^{-5} (0.804)	0.0002 (0.627)	8.9 × 10^{-5} (0.789)	0.0001 (0.736)	8.8 × 10^{-5} (0.800)
$\hat{\alpha}_0$	2.9 × 10^{-6} (0.003) ***	−0.444 (0.000) ***	4.6 × 10^{-6} (0.000) ***	3.2 × 10^{-5} (0.508)	-
$\hat{\alpha}_1$	0.064 (0.000) ***	0.129 (0.000) ***	0.005 (0.737)	0.054 (0.020) **	6.197 (0.000) ***
$\hat{\beta}_1$	0.904 (0.000) ***	0.963 (0.000) ***	0.884 (0.000) ***	0.894 (0.000) ***	−0.932 (0.000) ***
$\hat{\gamma}$	-	−0.082 (0.000) ***	-	-	-
$\hat{\pi}$	-	-	0.112 (0.000) ***	-	-
$\hat{\theta}$	-	-	-	0.711 (0.036) **	-
$\hat{\tau}$	-	-	-	1.570 (0.000) ***	-
$\hat{\varpi}$	-	-	-	-	9.1 × 10^{-5} (0.000) ***
$\hat{\xi}$	-	-	-	-	0.968 (0.000) ***
$\hat{\psi}$	-	-	-	-	0.063 (0.000) ***
$\hat{\alpha}_{SAD}$	2.6 × 10^{-9} (0.991)	−0.001 (0.850)	3.2 × 10^{-8} (0.907)	7.2 × 10^{-8} (0.964)	7.5 × 10^{-9} (0.981)
$\hat{\alpha}_{FALL}$	2.4 × 10^{-9} (0.993)	0.0004 (0.929)	−7.7 × 10^{-8} (0.830)	−3.6 × 10^{-7} (0.870)	0.006 (0.630)
t-dist DoF	6.143 (0.000) ***	6.498 (0.000) ***	6.467 (0.000) ***	6.540 (0.000) ***	6.197 (0.000) ***
Log L	6804.856	6814.064	6817.210	6818.253	6805.062
Q (15)	21.296 (0.128)	21.729 (0.115)	19.666 (0.185)	20.401 (0.157)	21.158 (0.098) *
Q^2 (15)	9.405 (0.855)	9.701 (0.838)	8.918 (0.882)	9.166 (0.869)	8.362 (0.908)

Note: *p*-values are given in parenthesis. *, **, and *** denote statistical significance on 10%, 5% and 1%. *p*-values besides the DoF for the *t*-distribution refer to the Wald test for the null hypothesis of DoF being equal to 30. Condition in C-GARCH $0 < \hat{\alpha}_1 + \hat{\beta}_1 < \hat{\xi} < 1$ is not met. Other models satisfy their respective restrictions. However, the original GARCH model exhibited lowest forecasting errors. Bolded values in gray cells denote significant *SAD* and/or *FALL* effects.

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