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Abstract

The purpose of this study is to examine the presence of various seasonalities – the Weekend effect, the January effect, as well as, the Halloween effect – in Central and Eastern Europe and to construct trading strategies in order to benefit from the Halloween effect. The authors employed two models: a simple dummy regression and the EGARCH model. The results illustrated that there is a strong Friday effect in Slovenia, and Monday effect in Latvia. In addition, the returns in January are significantly higher than in any other month of the year in Estonia. Next, the Halloween effect is found to be present in Ukraine, Estonia, and Serbia, and it proves to be beneficial to hold the market portfolio in the period from November to April and then switch to either gold or some risk free assets in Estonia and Ukraine. The additional return plausibly outweighs any reasonable transaction costs of up to 1% of the deal. The results comparing to previous research done on CEE were mixed and no uniformity on the topic is present.

Keywords: Seasonalities, stock markets, Central and Eastern Europe, GARCH, EGARCH

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1. Introduction

According to Fama (1970) efficient markets incorporate all available information to determine the asset value. However, numerous researchers have found empirical evidence of the possibility to earn higher returns and that this phenomenon has a calendar pattern, which is referred to as seasonalities. Up until now quite a few studies have been conducted in different time spans, different countries, and using various methods.

The oldest and most commonly detected seasonalities are Monday effect and January effect, though such seasonal return patterns as the Halloween effect is still gaining attention. The Halloween effect is the phenomenon that returns are lower in summer, more precisely in the period from May to October, therefore it is also called "Sell in May effect". The Halloween effect was first researched by Bouman and Jacobsen in 2002.

The results are not uniform in all markets – presence of seasonalities differs among developed and developing countries as well as the time period chosen. These findings put in doubt that markets are even weak form efficient – past information on prices and returns actually can be used to some extent to determine future values of stocks, thus suggesting that past information is not fully incorporated into present prices.

Research on the Central and Eastern Europe (hereinafter referred to as CEE) – emerging markets – has been conducted only a little; hence, it is in the interest of the authors to study this phenomenon in CEE. The authors will develop an overview of seasonal return patterns of Central and Eastern European markets and in addition to the traditionally examined anomalies – the Monday effect and the January effect, the authors will also inspect the Halloween effect, which in current literature has received relatively little attention.

Moreover, most recent literature has changed a focus from just detecting various kinds of calendar patterns in different countries and in different time periods to new directions of investigations: some are trying to construct investment strategies, taking into account transaction costs, and others are focusing more on explanations of existing seasonalities. This split occurs due to different incentives – investors are mainly concerned about the usability of the empirical findings in the development of investment strategies, while scholars are more up to finding proof to market inefficiency or question the validity of asset pricing theories (Robinson, 2005). Bearing the latter in mind, the authors will attempt to construct a strategy intended to exploit the

Halloween effect in markets, where it will be present, in order to give ground to new investment vehicles and make use of the existing literature on seasonalities.

Another important aspect of why to conduct a research on market efficiency apart from academic and business interest is the fact that efficiency of capital markets in developing countries plays a crucial role for economic development (Robinson, 2005). *"Developing countries typically face financial and other constraints that are not binding for developed countries. Such financial constraints are inter alia low domestic savings ratios and limited access to interactional capital markets,"* claims Singh (1995).

Hence, the authors have come up with the following research question: *Is it possible to benefit from seasonalities in Central and Eastern Europe?* This implies that the authors will, first, detect the types of seasonalities present in CEE and then develop trading strategies to gain from seasonalities. The studied time frame will be from January 2000 to early 2012, yet the authors note that because of the peculiarity of the countries under study, the time sample will vary across countries. Additionally, in order to enhance the validity of the research, the authors will use two different models to determine the seasonalities.

The limitations to this research are data availability and time span of the capital markets of CEE. Plus, seasonality explanations are out of the scope of this research, because the authors will focus on the practical usability of the findings.

The paper is structured as follows: the first section presents the literature review on the topic. Next the authors describe the data and develop the methodology of the study. Further on, the empirical results of the research are presented, which are followed by a thorough discussion. The authors end with conclusions and further implications.

2. Literature Review

The vast amount of academic literature devoted to seasonalities mainly concentrates on the violations of random walk in returns (implying return predictability) in calendar turning points (Robinson, 2005). This literature on seasonalities in market characteristics can be distinguished into three groups: studies focusing on a single market with long time-series, studies using a large cross-sectional data, and a mix of the former and latter. The first type tries to test whether past information can be used as a predictor for future stock movements. The second studies whether one phenomenon is present in various markets around the world. Finally, the last one focuses, as one can assume, on cross-sectional existence and predictability of stocks. In this research authors will concentrate more on the phenomenon presence in different markets.

2.1. January Effect

The inception of the literature about the January effect is attributable to the end of 1970s, and it refers to the phenomenon that returns in January in many stock markets were found to be higher than in any other month. Rozeff and Kinny (1976) were the pioneers when it comes to the January specific anomalies in returns of small stocks. They dicovered that returns in January were substantially higher in comparison to other months.

At the time it was a common belief that the January effect was attributable to small stocks only. For example Keim (1983) studied the New York Stock Exchange (NYSE) and American Stock Exchange (AMEX) common stocks and found that the turn-of-the-year effect exists only in small cap stocks, and that the anomaly is size related. The author found that there is negative relationship between excess return and size of the stock, meaning that small stocks experience a higher January premium, moreover more than halve of it comes from the first trading week.

The January effect has long time been attributed to small stocks only. Yet the study of Ackert and Athanassakos (2000) found that this belief is wrong and, in fact, visibility of the stock is what matters, while size and price were wrongly capturing the effect of visibility. Authors claim that after controlling for visibility (being widely followed), firm size becomes an insignificant determinant of seasonalities.

Gultekin and Gultekin expanded the research to an international level and found strong evidence which support the presence of this seasonality in majority of stock markets worldwide. The January effect is found to be consistent with turn of the tax year, which is why the April effect instead of January effect was detected in the UK (Gultekin & Gultekin, 1983).

The January effect is not only present in developed stock markets, there also is evidence collected from different kind of emerging markets. For example, Koh and Wong (2000) (as cited in Robinson, 2005) who studied this seasonality in seven Asian markets came to the conclusion that the January effect is present in two of these markets – Malaysia and Singapore. However, both countries do not tax capital gains, thus the detected seasonality contradicts the commonly accepted theory behind the January effect – tax-loss selling. Tax loss selling means that investors capitalize a loss on a stock in December and buy back the stock in January.

Regarding emerging markets, research still continues. Al-Rjoub (2004a) explored the emerging markets from different parts of the world, thirty five countries in total. Results are in favour of absence of the January effect for all countries in the sample except for Slovakia. Moreover, in 10 countries some other month was performing significantly better than January, which brings into doubt the existence of the January effect on stock exchanges in emerging markets.

Robinson (2005), using the sample period 1992-2001, explored the Jamaica Stock Exchange (JSE) in particular and arrived to the conclusion that returns were statistically equal in all months. These results contradict the ones obtained by Gultekin and Gultekin in 1983; however they are consistent with more up to date research. Robinson (2005) also concluded that despite the detected predictability of returns in JSE, one cannot claim that the patterns present in developed market translate to developing markets.

Lakonishok and Smidt (1988) looked on the long-term perspective and explored the seasonalities on Dow Jones Industrial Average (DJIA) index in a 90 year period. The authors found a constantly present January effect (along with the turn of the week effect, the turn of the month and holiday effect). The authors did not exclude the possibility that this has happened by chance, yet one has to admit that this is highly unlikely.

According to Nisser and Valla (2006), seasonalities have a property of changing over time. They examined seasonalities on Dow Jones Industrial Average (DJIA), Standard & Poor's 500 (S&P 500), NYSE, Financial Times Stock Exchange (FTSE), and some other stock markets and indices before and after the release of the publication about the existence of such seasonal patterns. The authors found strong support in favour of the hypothesis that seasonal effects (except for the turn-of-the-month effect) weaken or disappear after the published research about the presence of a particular seasonality in the market. Authors also come to the conclusion that that seasonality disappearance occurs right after the time of its discovery.

2.1.1. January effect rationale

One of the most famous seasonal anomalies – the January effect – usually has various explanations, yet if they were good enough the phenomenon would not have remained a puzzle (if one believes it actually exists).

Kim (2010) argued that the increased returns in January might be just a risk premium for the uncertainty around earnings announcements. Together with his previous work (Kim, 2006) this paper is one of the few to perform risk-based analysis of the January effect. He used an earnings volatility factor in his regressions and claimed that the previous findings of the phenomenon appeared due to a misspecified risk adjusting model.

Nevertheless, the most popular explanation lies within the tax-loss selling hypothesis. Chan (1986) argued that the January effect is associated with losses in stocks, yet his study did not clearly show that price pressure is caused by tax-loss selling. Yet his results were inconclusive on whether the reduced prices in January are directly caused by tax-loss selling. Additionally, Poterba and Weisbenner (2001) pointed out that individual investors contribute to the turn-of-the-year effect. However, still no direct cause and effect relationship has been set to explain the puzzle. Haug and Hirschey (2006) also attribute the January effect to the tax-loss selling, yet because they fail to prove any other possible solution.

All in all, for more than 30 years, scholars who believe in the presence of this seasonality cannot reach a consensus about the true cause and effect relationship of the mysterious happening.

2.2. Weekend Effect

One of the first researchers to explore the day-of-the-week pattern in stock returns was Cross (1973) who detected seasonal patterns on Monday and Friday returns. The author inspected the S&P Composite Stock Index, DJIA and NYSE Composite Index and found that results are very similar across these indices – returns are persistently higher on Fridays and lower on Mondays, moreover Monday returns are highly dependent on Friday ones.

Later French (1980) re-examined this issue using the same Standard & Poor's Composite Stock Index, and he confirmed the previous results of Cross about the constantly lower returns on Mondays. French also compared Monday returns with post-holiday returns to examine whether the Monday effect is simply the result of closed markets, and he came to the conclusion that negative Monday returns are driven by the weekend effect, rather than closed market effect.

Gibbons and Hess (1981) provide further empirical findings in favour of persistently low or even negative returns on Mondays in US stocks. Authors also explore seasonal patterns in risk-adjusted returns and conclude that seasonality in Monday returns is no longer there.

Robinson (2005) explored 58 stocks on JSE and concluded that there is no empirical evidence to support day-of-the-week effect in majority of JSE stocks, which is a quite plausible conclusion as seasonalities in emerging markets tend to differ from the ones present in developed markets.

Flannery and Protopapadakis (1988) also found that day-of-the-week seasonalities also exist in the derivatives' markets which contain stocks as the underlying assets, as well as, in bond markets, moreover Monday returns are even lower for instruments with longer maturity.

According to Elango and Al Macki (2008), who investigated the presence of seasonal patterns in returns of three major stocks in the National Stock Exchange in India (NSE), there are mixed evidence of negative Monday returns – two out of three stocks support the weekend effect. The unexpected finding was that returns are the highest on Wednesdays, not on the commonly accepted Fridays.

Al-Rjoub (2004b) also tried to take into account the measurement errors and increase the sample size, yet he arrived at the same conclusion – the weekend effect is still present which is consistent with previous research, however the highest returns are detected on Thursdays.

Based on this so famous seasonality, Yale Hirsch (1986) wrote a book *"Don't sell stock on Monday"* where the author proposes the best days of the week, best months of the year to perform particular trading activities, yet as pointed out by the critics there are no in depth explanations.

2.2.1. Weekend effect rationale

Most popular explanation for the day-of-the-week effect so far is the lag in responses to macroeconomic news. For example Chang et al (1998) attributed this phenomenon to the main part of the day-of-the-week effect present in equity returns.

Rystrom and Benson (1989) stated that purely from a behavioural perspective individual investors are less optimistic on Mondays. Abraham and Ikenberry (1994) offered another explanation for the Monday effect, suggesting that it is driven by individual investors mainly as this type of investors most actively close their positions on Mondays after spread of bad news in the market during the weekend.

On the other hand Sias and Starks (1995) claimed that institutional investors are the ones who are responsible for the Monday anomaly. Bell and Levin (1998) also tried to relate the explanations of day-of-the-week effects to institutional factors, such as the reluctance to hold excess cash in the periods of closed markets.

Another perspective on the cause of the day-of-the-week effect is employed by Chen et al. (2003) who claim that short sellers cause this type of seasonality as they are the ones who are the least willing to hold their positions over a long time period. Short sellers are most likely to close their positions on Fridays and reopen them on Mondays, thus making Friday returns higher than Monday.

2.3. Halloween Effect

The topic of the Halloween effect (in other words, from November to April returns on stocks are higher than for the rest of the year) is a relatively new concept comparing to other seasonalities in market characteristics like the January effect or the Monday effect. However, there are already numerous papers done in this field which quested to find additional returns and try to use them to earn profits using past information.

Bouman and Jacobsen (2002) studied this phenomenon in 37 different countries and reported support of the existence of this seasonality in 36 markets. They concluded that the old saying *"Sell in May and go away!"* holds and interestingly enough this anomaly can be traced, for instance, in the UK as far back as 1694. The effect is reported to be especially significant in Europe and it exhibits time-invariance. Results appear to be similar if instead of October, the month of September is being employed. For most countries returns in the November-April period proved to be large, yet May-October ones not statistically different from zero or even below that threshold.

Bouman and Jacobsen (2002) also presented possible explanations of the contradictory result to the efficient market hypothesis, yet did not fully explain the puzzle. They overconfidently ruled out most popular reasoning for this effect, namely, data mining, the

January effect or risk explanations and presented that the cause was the summer months, as well as, vacations. Interestingly, they found in their study that the Halloween effect is not sector specific which is in contrast to other studies.

All in all, the authors suggested that the way how to gain from this phenomenon would be to hold the market portfolio starting from November and ending in April and then investing in the risk-free assets. Their method, according to the study, would be superior to holding the market portfolio throughout the year, implying that an investor could beat the market on a risk-adjusted basis. However, after bearing in mind the transaction costs, the authors find that this strategy cannot be economically beneficial in most cases. This is still contradictory to the findings of Lucey and Zhao (2008) that the Halloween effect is merely an overspill of the previously discussed January effect. In addition, Lucey and Zhao find that the findings of Bouman and Jacobsen (2002) are not good predictors that could determine future movement of stocks, in particular greater ones.

Maberly and Pierce (2003) tested the Halloween effect presence in Japanese equities, and according to them the crucial feature that Bouman and Jacobsen did not account in their study for was the distinction between *bull* and *bear* markets, meaning some years are considered to be the former, and some – the latter.

In their research Maberly and Pierce found that in Nikkei 225 during a bear market there is no statistical difference between May-October and November-April returns. In addition, returns in November-April in bear markets are more negative comparing to the bull market.

The study concluded that relative difference of a greater positive return in bear markets in November-April and a more negative return in bear markets in May-October cannot be profitably exploited due to transaction costs that the investor faces. In addition, the Halloween effect was only present in Nikkei 225 prior to internationalization of the financial markets and only in the bear markets. Nevertheless, the returns in bull market years were statistically higher in the November-April period comparing to the rest of the year, yet the authors suggested that even an ex-ante determination of a bull year would not be optimal.

Contrary to the study of Bouman and Jacobsen (2002) that recognized that the Halloween effect was not sector specific, a study by one of the authors with another researcher (Jacobsen and Visaltanachoti, 2009) found out that the "Sell in May and go away" phenomenon is sector related.

They discovered that the Halloween effect is almost non-existent in the consumer consumption sector, yet huge in production. Their research focused on US data from 1926-2006 using 49 industries and all stock market sectors and provided evidence that the anomaly has been persistent since its discovery in 1998. The debatable discovery of sector and industry specific anomaly furthers the problem of finding the true cause of this phenomenon.

Jacobsen and Visaltanachoti (2009) opposed Maberly and Pierce (2003) idea that the Halloween effect strategy cannot be exploited and argue that switching portfolio between industries can help to beat the general market portfolio.

The authors also enriched the literature by providing more evidence of the Halloween effect persistency and by examining the relation of seasonality of liquidity and market returns. They found that the Halloween effect is not induced by varying liquidity, neither in the general market, nor sector specific. However, they lacked to give explanations to this phenomenon as suggested by Doeswijk (2009) who reckons that there is a link between the seasonality in the sector with the optimism cycle hypothesis.

2.3.1. Halloween effect rationale

Bouman and Jacobsen (2002) studied the Halloween effect and stated that they had found a link between summer vacation periods and the “Sell in May and go away” phenomenon. Most probably during summer traders’ absence reduces total volume bought and sold, thus lessening the chance of investors to short or long the asset they desire.

Jacobsen and Visaltanachoti (2009) listed also several other explanations about what could be the reasons of the Halloween effect, yet it dealt with sector differences. They said that any economic activity that is seasonal and affects stock prices varies around different sectors because, for instance, Christmas shopping and the school year does not affect all companies similarly.

Doeswijk (2009) criticized the latter explanations because it did not include his own developed optimism-cycle hypothesis. The idea behind it is that investors tend to buy cyclical stocks that react to overall economy very much in autumn due to optimistic expectations about the next year. Yet in late spring this optimism fades away and people switch to defensive stocks.

After so much of extensive research about calendar patterns in returns there is no question about the existence of those seasonalities. As suggested by Jacobs and Levy (1988), economic significance of these seasonal patterns is very limited, and the real reason behind these anomalies is purely behavioural. They also suggest that psychology should do the best at explaining seasonalities in stock returns.

3. Data Description

The main data used in this study was attained from the Thomson Reuters Datastream database and Bloomberg Terminal database for the period from January 3, 2000 to January 25, 2012. For the purpose of this study the authors used the Total Return Index, which is a market index adjusted for the outstanding share amount and dividend payments. The formula is provided below.

$$TRIndexPrice_t = TRIndexPrice_{t-1} \text{x} \frac{\sum_{i=1}^{n}[(p_{i,t}\ x\ h_{i,t}\ x\ r_{i,t}) + (div_{i,t}\ x\ h_{i,t}\ x\ r_{i,t})]}{\sum_{i=1}^{n}(p_{i,t-1}\ x\ h_{i,t-1}\ x\ r_{i,t-1})}$$

where: $p_{i,t}$ = price of equity i = 1,2,...n, at time t=0,1,2,...,T and t=0 means the initial time period,

n = the number of equities in the index

h = the number shares in equity i at time t == $q_{i,t}$ or $s_{i,t}$ depending on whether MC or EQ weighting is used respectively,

$$r_{i,t} = \begin{cases} 1, \text{if a country index} \\ \text{exchange rate from local currency to USD at time t, if a regional index} \end{cases}$$

$div_{i,t}$ = per share dividend on ex-date

Further on, the authors calculated the daily and monthly returns of Total Return Market Indices, using the following formula:

$$r_t = \ln\left(\frac{TRIndexPrice_t}{TRIndexPrice_{t-1}}\right) x\ 100$$

where: r_t	the return on *Total Return Index Price* on day or month *t*
$TRIndexPrice_t$	the closing price of the *Index* on day or month *t*
$TRIndexPrice_{t-1}$	the closing price of the *Index* on day or month *t-1*

The list of the indices that were used as a market proxy for total adjusted returns is summarised in Appendix A (table 1). The choice of a particular index for a country was determined by priorities, where the number one was the national stock exchange data, which was followed by MSCI, S&P, DJIA and other index calculating company figures. Additionally, the authors tried to attain adjusted stock index price in national currency, yet where it was not possible, they chose either Euro or USD denominated data. For convenience, the authors will refer to a country's Total Market Return index not by its full name but rather by just a particular country's index (e.g. DJTM BULGARIA $ will be referred to as Bulgaria Index).

4. Methodology

4.1. Detecting Seasonalities

4.1.1. Dummy variable model

In order to test the existence of all seasonal effects described above, the authors use the most popular dummy variable framework. This technique can be seen as a mean comparison between stock returns in different time periods of interest.

To test the month-of-the-year effect, most common of which is the January effect, the authors incorporate month-specific dummy variables $M_2 \dots M_{12}$ (where 2 represents February dummy, 3 – March etc.) into the following regression:

$$r_t = \beta_0 + \beta_1 M_{2t} + \beta_2 M_{3t} + \beta_3 M_{4t} + \beta_4 M_{5t} + \beta_5 M_{6t} + \beta_6 M_{7t} + \beta_7 M_{8t} + \beta_8 M_{9t} + \beta_9 M_{10t} + \beta_{10} M_{11t} + \beta_{11} M_{12t} + \varepsilon_t,$$

where β_0 is a constant and ε_t – error term.

Variable M_2 takes a value of 1, if the specific day falls into February and 0 otherwise, same with other month variables. To avoid the dummy variable trap, one dummy variable has to be excluded from the regression. In this particular regression January is excluded, meaning that this specification is for testing the January effect. Coefficients on all other month variables (β_1-β_{11}) being significantly negative would allow the authors to reject the null hypothesis of no January effect. One has to understand that in this kind of regression the constant represents the average January return, while all other betas show the difference between the excluded month (January) and the particular month attributable to each beta.

To test the day-of-the-week effect, the authors created 5 day-specific dummy variables $D_1 \dots D_5$, where 1 stands for Monday, 2 – Tuesday etc. Regression for testing Monday effect would look like this:

$$r_t = \beta_0 + \beta_1 D_{2t} + \beta_2 D_{3t} + \beta_3 D_{4t} + \beta_4 D_{5t} + \varepsilon_t.$$

Variable D_1 takes a value of 1 if the specific day falls into Monday and 0 otherwise, same with other day variables. Again, one dummy (in this case D_1) variable has to be excluded from the regression. If coefficients on all day variables (β_1- β_4) are significantly positive, it implies that Monday returns are lower than any other day returns, signalling a strong Monday effect. To test the Friday effect, the Friday dummy variable (D_5) is dropped. In this case the authors will be able to reject the null hypothesis of no Friday effect, if all beta coefficients before the dummies are significantly negative.

The very same regression technique is used to examine the Halloween effect. Similarly as previous, a dummy variable is created – seasonal (Halloween) dummy W_t. The seasonal dummy is 1 if the day falls in the period from November till April (winter period), and 0 otherwise.

$$r_t = \beta_0 + \beta_1 W_t + \varepsilon_t.$$

If the Halloween effect exists, then β_1 should be significantly positive, indicating that average returns in the period from November to April are higher than in other months. Afterwards, an adjusted regression on the Halloween regression is performed where January is excluded from the winter period and added into the regression as a separate dummy variable in order to see, whether the Halloween effect is driven solely by the January effect. In case the statistical significance of the winter dummy disappears, while the January dummy turns out significant, there is evidence that average winter period return seems to be higher than summer period return just because of high January returns.

What has to be noted is that in case of the coefficients before all dummy variables are 0, return pattern transforms into the random walk model $r_t = \beta_0 + \varepsilon_t$ which implies no return predictability (no seasonal patterns).

4.1.2. Exponential GARCH model

Autoregressive conditional heteroskedasticity (ARCH) family models are typically used to study the financial markets, e.g. foreign exchange and stock markets, and other financial data. As the name suggests, these models account for heteroskedasticity and autocorrelation in time-series and cross-sectional data. ARCH family models have been used in numerous previous research on stock market characteristics, for instance, Baillie and DeGennaro (1990) used the Generalized ARCH model (GARCH) to examine the relationship between stock returns and volatility. Faff and McKenzie (2002) also employed GARCH to model country returns to explore daily seasonalities in 7 developed countries.

However, to test the same effect in both returns and the conditional variance Savva et al. (2005) employed the Exponential GARCH (EGARCH). Also, Vu and Urrutia (2006) employ this model to study the randomness in American Depository Receipts (ADR) returns.

EGARCH is particularly useful to this study, since this model specification addresses the following issues: the excess kurtosis, volatility clustering, allows exogenous shocks to have asymmetric influence on the conditional variance, and drops non-negativity constraints of the previous models. (The Mathworks, 2004)

Excess kurtosis is a characteristic of the data when the returns exhibit fatter tails, meaning that outliers are more probable, than the standard normal distribution. Volatility clustering is a phenomenon in time-series data when the variance varies from one period to another. In simple terms, it just reflects that some moments in time exhibit more turbulence than others. This means that if the error term of the regression has small variance in one period, it will have a small one also in the next one; however the picture will reverse in some other period. Asymmetric influence on conditional variance is just a reckoned phenomenon that negative shocks influence the volatility more than positive shocks.

In addition, EGARCH employs a natural logarithm of the conditional variance and uses absolute values of the error terms, thus ensuring that there are no additional non-negativity constraints.

Since the authors possess daily time-series of just 11 years, the chosen specification for the EGARCH (p,q) model is EGARCH(1,1). The reason for this is presented by Engle (1982), who argues that higher order terms would be applicable for longer time horizons, for instance, a few decades or more.

In order to estimate any seasonality using the EGARCH model, first of all, the authors have to run the respective regression for every phenomenon as in the section *Dummy regression model*. Furthermore, the assumption behind the normal distribution of the error term remains unchanged, yet for convenience, the authors denote $\varepsilon_t \sim N(0, h_t)$, where h_t is a time varying conditional variance of the error term.

The selected specification of the model – EGARCH(1,1) – looks as follows:

$$\ln(h_t)=\gamma_1\,\varepsilon_{t-1}+\theta_1(|\varepsilon_{t-1}| - E|\,\varepsilon_{t-1}|) + \beta_1\ln(h_{t-1})$$

where β_1 denotes the persistence in volatility, θ_1 denotes the magnitude effect, and γ_1 depicts the presence of shock asymmetry (negative shocks increase volatility more than positive ones).

The authors note that statistical software incorporates the latter regression into the dummy variable regression, thus giving EGARCH regression estimates for dummies and ARCH-consistent standard errors. In this paper the usage of EGARCH model serves as a robustness check for seasonality patterns in market returns, not a tool for detecting seasonalities in market volatility, therefore no particular attention will be drawn to ARCH/GARCH parameters θ_1, β_1, and γ_1.

4.2. Trading Strategies

In order to depict the practical implications of seasonalities, the authors will construct trading strategies similar to Bouman and Jacobsen (2002) for countries where these phenomena are present in order to test the mean-variance efficiency of market indices and see if it can be superior to the market portfolio, and if it can profitable to do so. The main idea of the strategy is that the investor holds the market portfolio when the seasonality is present and after that allocates his funds to the so called 'safe haven' assets.

In particular, the authors will attempt to exploit the Halloween effect, because portfolio rebalancing is costly and switching assets on a weekly or monthly basis would pile up huge transaction costs and hamper the return. Since the strategy to earn on behalf of the Halloween effect would require to rebalance the holdings only twice a year, it is likely that expenses incurred while performing these particular financial operations can be outweighed by the additional profit.

The authors will create and calculate the average returns (similarly as in the previous section) and volatility of the portfolios used by Bouman and Jacobsen (2002) and for one additional one:

Buy and Hold strategy:	the investor holds the market portfolio throughout the year;
Halloween strategy:	the investor holds the market portfolio in the period from November to May and then switches to risk free assets;
Gold strategy:	similar to the Halloween strategy, yet the investor acquires physical gold instead of risk free assets;

For future notice, the authors will refer to the Halloween and Gold strategies as trading strategies and Buy and Hold strategy will be called as holding the market portfolio or just the market.

Next, in order to test the mean-variance efficiency of the Halloween strategy and Gold strategy the authors will use the following regression:

$$r_t^p - r_t^f = \alpha + \beta_1\left(r_t^m - r_t^f\right) + \varepsilon_t$$

where r_t^p denotes the annual return on the particular portfolio, r_t^f denotes the annual risk-free rate, r_t^m stands for the appropriate annual return of the particular countries market index and $\varepsilon_t = r_t^p - E_{t-1}[r_t^p]$, whereas α stands for the above the market return, also known as the Jensen's alpha and β_1 depicts the sensitivity of the portfolio to the market.

The regression results will allow to make comparison to the market of the trading strategies' returns and riskiness, as well as, to examine whether they mean-variance dominate the respective country's index.

The Halloween strategy and Gold strategy annual returns will be calculated as the cumulative return starting from January to the beginning of May, then increased by the appropriate selected asset return in the period from May to November, and finally the market return in November to December will be added.

For prudence, the authors will use the same dates (day specific) for asset switching in May and November for the two aforementioned strategies. The authors will use 6M EURIBOR as the risk free rate proxy. Return on investment into gold will be calculated similarly as for the index returns.

The authors chose to add another – Gold strategy – portfolio to the ones of Bouman and Jacobsen (2002), because historically gold has been a wealth accumulating asset. However, because of recent discussions about the real value of gold and does it have a bubble, the authors note that the crucial trading strategy they would like to test is the Halloween strategy.

5. Empirical Findings

5.1. Preliminary Statistics

In this section the authors intend to review the statistical characteristics of the indices' return variables for CEE countries. The reasoning behind the data review is quite simple – to explore the data and examine the normality of the data.

Firstly, we review the statistics presented in the Appendix B, table 2. One can clearly see that average daily return for all CEE countries except Hungary and Serbia is positive, however negative returns for these two countries can be explained by much shorter time period of data available. The standard deviation is huge, indicating a high level of volatility in the stock market indices. Knowing that our sample period consists of a period of high growth, as well as, a period of global downturn, the authors conclude that low mean returns and high standard deviations are quite plausible. Average growth of indices during the period was a bit more than 3 basis points per day, which comprises an annualized above 8%. From the table one can also notice that Bulgaria Index yielded on average the highest returns during the period under study, yet again this is not that comparable due to shorter data period.

The table also contains the information on skewness and kurtosis of the return variables. The kurtosis of normally distributed variable should be around 3. One can clearly see that kurtosis for stock indices returns are way more than the kurtosis of normally distributed variable. Actually, kurtosis is high for all indices returns in our sample, thus it would be reasonable to conclude that all markets are subject to extreme observations, however there is one notable outlier – Bulgaria. The closest to normal kurtosis is Poland, which makes sense as it is the most developed financial market in the sample. By looking at the skewness of the returns, which should be 0 for normally distributed variables, authors see that negative skewness in half of the countries signals that negative returns were occurring there more often than positive ones, and vice versa for other market indices. In terms of skewness, particular outliers are Bulgaria and Ukraine.

Or preliminary statistics show that the return variables are not entirely normally distributed, therefore the authors carry out the variable transformation test. This test is performed in order to test which variable form specification would deliver the most normally distributed variable. According to this test, the best option is to leave return variables as they are which could be quite reasonable, as returns are already in logarithmic form. Moreover, none of the previous studies reported the necessity of variable transformation.

Authors also take a closer look on return volatility. Just for visual purpose returns over time are plotted for some countries (Appendix B, figures 1-5). One can see that volatility is definitely not constant over time, where, apart from other rare occasions, notably higher volatility is visible during global financial crisis period starting from 2008.

To conclude, the authors consider time-variant volatility, which signals about autoregressive movements in variance process, as well as, the excess kurtosis to be an indication that our data candidate for ARCH family models for the robustness check.

5.2. Preliminary Seasonality Recognition

5.2.1. Days of the week

Daily figures that will be used for the Weekend effect examination are preliminary explored (Appendix B table 3). Here one can see that the average Monday daily return is negative in 8 out of 13countries, however the magnitude of those negative averages varies from 0.1 basis points in Slovakia to 21 basis points in Bulgaria. Interestingly enough, the average Tuesday return is negative in even more countries. The day in which average returns are positive in the highest number of countries, of course, is Friday.

No clear trend is detected with the exception of the fact the returns tend to be higher in the second part of the week in comparison to Monday and Tuesday. Interestingly enough, every country has its own day with the highest return, and only in 7 countries this day is Friday.

From the table one can also notice that candidates for the Monday effect are Bulgaria, Croatia and Latvia with highly negative Monday returns below other day returns, while candidates for Friday effect are Estonia, Lithuania and Ukraine with positive Friday returns above other day returns.

5.2.2. Months of the year

The authors also examine average daily returns in different months (Appendix B table 4) and note that average daily return is positive in 10 countries. The highest January daily return is detected in Estonia – 0.26 basis points a day, which is an annualized return of 65%, assuming 250 trading days.

The authors also notice three potential countries for the January effect – Estonia, Lithuania, and Serbia, as the average daily return in January in those countries is much higher than in any other month. As for other countries, there is no one particular month with the highest return – returns are the highest in September in Bulgaria, December in Czech Republic, July in Latvia etc., thus no overall January effect seems to be present.

5.2.3. Half-year periods

The figure below (chart 1) illustrates average half year returns in 13 CEE countries. The economically significant Halloween pattern (return in winter season is much higher than return in summer season) is clearly seen in Poland, Romania, Slovakia and especially in the Czech Republic, Estonia, Hungary and Ukraine, where average summer period returns are negative while winter period returns are substantially positive. The economic difference is huge – for example ~5.5% difference in summer and winter returns transforms into 11% annualized return difference. In the country with the most pronounced Halloween effect – Ukraine – this difference is 8 times larger.

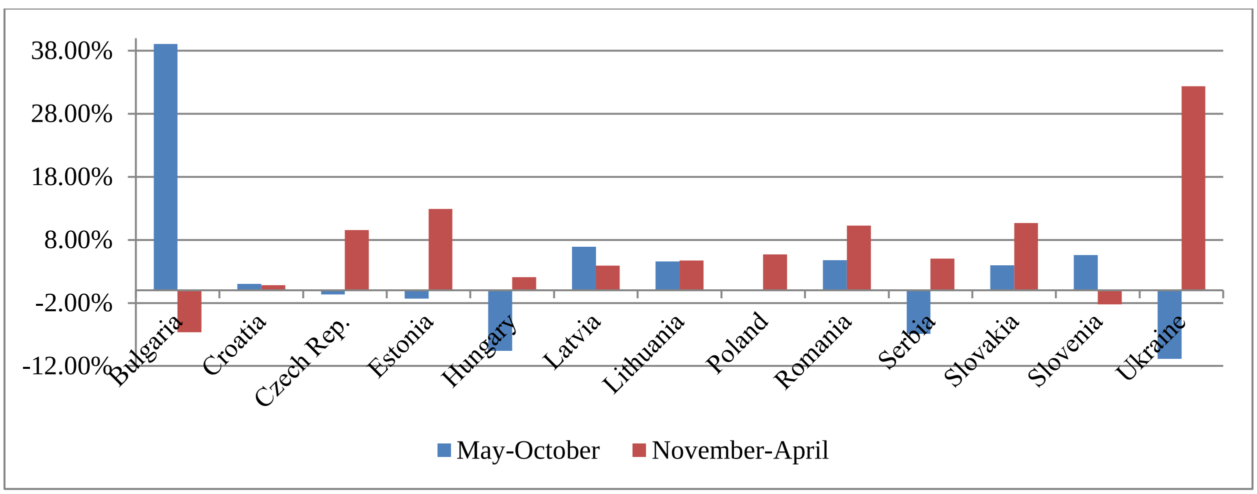


Chart 1 *Average 6 month returns in the periods of May-October and November-April across countries*
Source: created by the authors based on data from Thomson Reuters and Bloomberg Terminal (2012)

The graph also clearly shows that two period average stock returns in some countries indicate an opposite Halloween effect (for convenience it will be called *the reverse Halloween effect*), when summer returns appear to be substantially higher than the winter ones, and those countries are Bulgaria, Slovenia and Latvia, yet the economic significance of the latter one is somewhat less pronounced. Thus, the authors suspect the existence of reverse Halloween effect, not specifically studied in academic literature.

Even though only economically significant differences are provided, the chart, at this stage, shows some indications that statistical significance will go in line with economic significance in at least some countries regarding the Halloween effect phenomenon. Therefore, in the next section, the authors provide statistical evidence for the effects under study.

5.3. Regression Analysis

5.3.1. Weekend effect

In this section the authors examine the Weekend effect in the selected countries in order to determine whether this phenomenon is present and how strong it is. The literature which has found the seasonality suggests that on average returns tend to be lower on Mondays and in contrast higher on Fridays.

It is crucial to understand the interpretation of the given tables (Appendix C tables 5 and 6). As one dummy variable is excluded from the regression, the coefficients for the days of the week represent the difference between the particular day's return and the excluded day's average return, which is incorporated in the constant term. The constant is the average daily return for Monday (in the Monday effect output, table 5) and average daily return for Friday (in the Friday effect output, table 6). The authors consider two and less week days with statistically insignificant difference from the constant to signal of no evidence of the Monday or Friday effect existence.

The evidence exhibit that in Latvia returns on Wednesdays, Thursdays, and Fridays are statistically significantly higher than on Mondays (Appendix C table 5). The level of significance of these results is either 5% or 10%. Returns on Mondays appear to average zero. The differences between Monday and other weekdays are rather large, from 8.6 to 20.4 basis points per day. To put it an annual term perspective average of ~16 basis points a day yield a return of around 40%, assuming 250 trading days, which is substantial. Even though returns on Tuesdays are not significantly different from the constant, the authors still conclude that there is evidence of presence of the Monday effect in Latvia, as economic significance of Monday and Tuesday returns is still present.

As for the stock market in Croatia, it also illustrates a quite strong yet still not perfect Monday effect – all weekday returns are statistically significantly higher than Monday returns except Thursdays'. Monday returns are significantly negative in both statistical and economic sense. Despite Thursdays not proving to statistically outperform Mondays, the authors still conclude that there is presence of the Monday effect in Croatia, as the difference of more than 20 basis points between Monday and Thursday average returns makes it plausible to assume that the difference is out there.

Even though Wednesday and Thursday returns appear to be the same as on Mondays, Bulgaria stock returns illustrate characteristics of the Monday effect to some extent, meaning that returns on Tuesdays and Fridays are significantly higher. Additionally, Monday is the only week day when average returns are statistically significantly below zero, which further supports the hypothesis of bad Monday performance in terms of returns. However, the authors consider this evidence not strong enough to claim the existence of Monday effect in Bulgaria.

The authors decided to disregard the single significant Friday coefficients in Slovenia and Ukraine and thus to conclude that no signs of the Monday effect exist in stock returns of those two countries. Presence of other negative coefficients other than for Monday further supports this conclusion.

The robustness check with the ARCH family model described in the methodology does not support the above mentioned Monday effect for Croatia, as only Wednesday returns remain significantly above Monday ones with coefficient before Wednesday dummy being 0.1956 (p-value 0.033), which is quite similar to the result obtained by the simple dummy regression. Regarding the presence of the Monday effect in Latvia, EGARCH model estimates three significant coefficients, as well as, a significantly negative constant (Monday returns). Yet, the model could not estimate the standard error of Thursday coefficient due to some reason unknown to the authors. All other coefficients are significant at least at 5%, which in authors' opinion serves as evidence in support of the previous conclusion about the presence of the effect in Latvia.

Alternatively to the Monday effect, which was found in two countries to some extent, the Friday effect was detected in Slovenia (Appendix C table 6). It has to be mentioned that Slovenia exhibits the Friday effect in its classic way according to the theory – firstly, significantly positive constant reflecting above zero Friday returns, and secondly, significantly negative all other week day coefficients implying that other day returns are significantly lower than Friday returns.

Despite the noteworthy economic difference (50-60 basis points difference between Friday and other days returns), evidence in the Ukrainian market is considered to be not enough to conclude the presence of the Friday effect as Tuesday and Wednesday returns do not differ statistically from Friday returns.

Similarly as with the Monday effect, the authors compare the results above with the EGARCH regression output. Again, one weekday coefficient for Slovenia could not be estimated by the software, yet other coefficients are all with the same signs and significance levels (1%) as in a simple dummy variable regression. Moreover, all numeric values of coefficients in EGARCH regression do not deviate from coefficients in simple regression by more than 2 basis points, which indicate that both models lead to the same conclusion about the presence of the seasonality in Slovenia.

What needs to be mentioned is that even though the ARCH/GARCH parameter estimates are not of particular interest in this paper, they are still statistically significant, especially ARCH parameters, indicating of existence of autocorrelation problems in the dataset which is to some extent tackled by the EGARCH regression.

5.3.2. January effect

The data illustrates quite strong evidence of the January effect presence in Estonia (see Appendix C table 7). Average daily returns in all months with some exceptions are 20-30 basis points lower than in January. The average daily return in January was almost 27 basis points, which is a notable 6% return per one month assuming 21 trading days. Regarding the significance of the regression coefficients, one can see that, firstly, all month average returns are below the one of January (all signs – negative), secondly, January return is both statistically and economically significantly positive and, finally, only two month returns do not statistically differ from January returns. All this allows the authors to conclude in favour of existence of January effect in Estonia.

The authors performed the EGARCH model regression for the January effect as well, and the results obtained in the Estonian market are consistent with the results above. Only one month, September in particular, loses its significance (now three months with insignificantly different returns from January – March, August, and September), which leaves eight months with significantly lower returns compared to January. On contrary, some other coefficients have its significance level increased. Additionally, all coefficient signs remain same (negative for month coefficients, positive for constant) except for March, which becomes positive compared to simple dummy variable regression. Yet, as March coefficient is insignificantly different from zero in both cases, it does not change the conclusion. Thus, the EGARCH model confirms the trustworthiness of the simple regression results.

Similar yet not so profound evidence of January effect is in another Baltic State – Lithuania. In six months out of eleven returns are significantly lower than in January when the daily returns averaged almost 18 basis points and proved to be statistically different from zero. Despite the significant constant and some bad performing months, the authors do not consider the existing evidence to be clear-cut, thus there is not enough empirical evidence to claim the existence of January effect in Lithuania, however it is also not plausible to exclude such possibility.

As for Lithuania, EGARCH regression results show seven significantly lower month returns compared to January, which is by one more than in simple regression. Additionally, all signs remain unchanged. This evidence suggests that both models lead to similar result, even though EGARCH model presents slightly more evidence in favour of January effect in Lithuania.

Serbia and Ukraine also exhibit statistically significantly positive returns in January. The mean daily returns in the first month of the year were 16 and 31 basis point, respectively, which were higher than average returns of all other months except for December in Ukraine. This gives a slight feeling of the presence of January effect in those countries, yet empirical evidence is very weak.

5.3.3. Halloween effect

The overall data illustrates weak statistical evidence in support of Halloween effect in CEE as statistical evidence of Halloween effect is present only in three countries – Ukraine, Estonia and Serbia with 1%, 5% and 10% level of significance, respectively (see Appendix C table 8). Results also seem to be quite economically significant, for example daily returns in the winter period are 8 and 11 basis points higher than returns in summer in Serbia and Estonia, respectively. Ukrainian stock index winter period average daily return is 31 basis points above the summer period. Those numbers comprise a huge return if annualised. Further on, one can notice that economic significance grows along with the statistical, which also makes sense.

Additionally, it is worth drawing more attention to Ukraine in particular, as the Halloween dummy is most economically and statistically significant, as well as, it is the only country where the summer period returns average below zero and are statistically significant. This makes the authors believe that Halloween effect is present in its most pronounced form in Ukraine – summer returns are very low (negative, in this case), while winter returns are considerably higher.

Regression results also show that average daily returns in the May-October period are not statistically different from zero in all countries in our sample, except in Ukraine as already discussed above. This indicates that even though Halloween effect is not statistically present in majority of countries, summer period average returns are still very low (close to zero).

Using the EGARCH model to test whether the Halloween effect results for Ukraine, Estonia and Serbia with simple regression are robust, the authors obtain very similar output. Signs of the coefficients remain the same and magnitudes did not change much as well, which is a good indicator. Winter coefficients now are all statistically significant at 1%, economic significance of Ukraine and Serbia coefficients increases by 10 and 2 basis points respectively, while it drops by 1.5 basis points for Estonia compared to simple regression. Ukraine loses the significance of its constant, implying that summer returns are not significantly negative but rather close to zero, however the constant for Serbia now appears significant. Yet, the particular interest is in winter season coefficients as they are the ones indicating of Halloween effect. The conclusion is that the EGARCH model supports the previously described evidence of higher winter returns in those countries.

As already mentioned in preliminary effect recognition, some countries might experience a reverse Halloween effect. One can clearly see that coefficients before winter period dummy are negative in such countries as Bulgaria, Latvia and Slovenia, implying that average daily returns are higher in summer period rather than in winter period in those particular countries. However, those negative coefficients are not statistically significant, thus nothing meaningful can actually be concluded, except the economically significant difference in Bulgaria. The authors find no statistical evidence in support of reverse Halloween effect.

In case of Latvia and Slovenia, same is confirmed by the EGARCH regression, where all coefficients remain statistically insignificant and numerically small. However, interesting results are obtained for Bulgaria in the EGARCH model – it presents highly statistically significant results in favour of the Halloween effect with both the winter coefficient and the constant being significant at 1%. This is an unanticipated result, as the signs of simple regression model coefficients indicate of a potential reverse Halloween effect, yet statistically insignificant. However, the winter coefficient in the EGARCH model appears to be very strange – the economic significance is immense (4% daily return difference in summer and winter period). Moreover, this is inconsistent with preliminary statistics of average half-year returns, where summer clearly outperforms winter, therefore the authors will consider Bulgaria as an outlier, and thus no meaningful conclusion will be drawn.

Taking into consideration the previously found evidence of presence of January effect, the authors created the adjusted winter dummy to see whether the Halloween effect is just a consequence of January effect or are these effects independent. The adjusted dummy consists of all previously included months (November-April) except January. The January dummy, logically, enters the regression separately as a control variable.

One can notice that Halloween effect disappears in Serbia when the January effect is controlled for, meaning that strong January effect is the only reason for existence of Halloween effect in Serbia (Appendix C table 9). This indicates that other winter period month returns except January are not that different from summer period returns. However, here two models exhibit inconsistencies, as the Halloween effect in Serbia remains strong after January adjustment if the authors use the EGARCH specification, yet this might be explained by the initial differences in models without January adjustment.

Regarding the Halloween effect in Estonia, the data presented that after excluding January from the winter period there is still statistical evidence that the average return in the winter period is above the average return in the summer period, however statistical significance drops from 5% to 10% level. This means that substantially positive January returns (1% significance level and large coefficient value in economic sense) do not fully account for the Halloween effect, even though January returns strengthen it. The authors conclude that after the adjustment the evidence in favour of the Halloween effect in Estonia is still present, meaning that other November-April period months contribute to this effect.

As for Ukraine, the Halloween effect is still highly statistically significant despite taking out the high and significantly positive returns of January. The economic effect dropped by 2 basis points, yet 29 basis points higher average daily return during the winter period as compared to the summer period is still considered to be an economically significant difference. The evidence presented above suggests that the conclusion about the strong Halloween effect in Ukraine is still valid.

The Halloween effect in Estonia and Ukraine despite excluding January still seems to be present in the EGARCH model as well, with higher significance of the winter coefficient in Estonia (at 1% compared to 10%) and lower significance in Ukraine (at 5% compared to 1%). Also, the EGARCH model shows no evidence of the existence of January effect in Ukraine; however, these minor changes do not impact the overall conclusion about the existence of the Halloween effect in Estonia and Ukraine even after excluding January from winter period.

5.4. Trading Strategies

The authors recognize that the trading strategy exploitation most probably holds in the sample period where the Halloween effect was detected. Hence, in order to test whether it is possible to benefit from the phenomenon, one would have to develop the trading strategy for a different time span in the same country. Due to data limitations that authors could not test the strategy in a different time period, yet they tested in on all 13 countries under study despite the presence of the effect only in 3 countries.

Six countries – Estonia, Hungary, Poland, Czech Republic, Serbia, and Ukraine (in this section further referred to as *the Countries)* – illustrated that the trading strategies returns were higher than the market total and they were economically significant (Appendix C table 10). However, in Poland only the Gold strategy had a larger return than the market, denoted in Appendix table 10

The Countries' (without Poland) average market return was 5.92% whereas for the Halloween strategy it was 11.49%. If we drop Ukraine, which had much higher returns than other countries, then the average for the four countries' market return was 3.01% and the mean for the Halloween strategy – 7.07%. The gap in returns is immense.

If we look at the Gold strategy then we see that the mean return for the Countries was 11.58% and their respective average market return was 5.89%. By dropping Ukraine we get that the average return of Estonia, the Czech Republic, Hungary, Poland, and Serbia Gold strategy was 7.81%, yet the market gained only 4.55%.

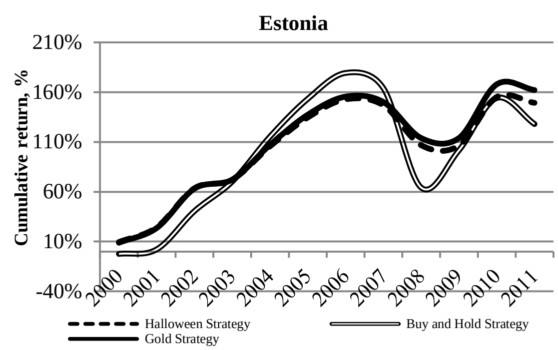
All six countries mean-variance dominated the market with the exception of Poland where only the Gold strategy was superior.

After illustrating the economic significance of the trading strategies, the authors checked for the statistical one.

It came as no surprise that the sensitivity (measured as the beta in the regression, which can be seen Appendix C tables 11 and 12) of both trading strategy portfolios to the market was lower than the market itself and was significant (Appendix C table 11 and 12). It happened due to the nature of the portfolio construction itself, meaning, that if I include risk free assets to my market portfolio, it becomes less risky and sensitive to the market. On the other hand, the constant – Jensen's alpha – was in the interest of the study, which is explored in the following paragraphs.

The Czech Republic and Estonia presented a statistically significant positive Jensen's alpha at 10% significance level and Ukraine depicted significance at 5% level (Appendix C table 11). The size of the alpha also remains economically relevant. Interestingly enough, Slovenia had a *reverse Halloween effect*, namely, a statistically significant negative alpha. This is a bit unexpected, as regression analysis did not find reverse Halloween effect to be statistically significant in Slovenia.

Similar results were attained also when testing the Gold strategy (see Appendix C table 12). The same three countries that illustrated a significant positive Jensen's alpha in the Halloween strategy also had one in this case, with the same levels of significance. Slovenia in gold strategy regression did not have an alpha statistically different from zero.



Graph 1 *Cumulative returns of various trading strategies in Estonia*
Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

For illustrative purposes the authors constructed graphs of Estonia, Serbia, and Ukraine cumulative returns of the strategies under study.

In Estonia the Halloween and Gold strategies went almost hand in hand and depicted lower growth and drops than the market. The trading strategies seemed better at all time, excluding the period of severe economic overheating in Estonia (2004-2007).

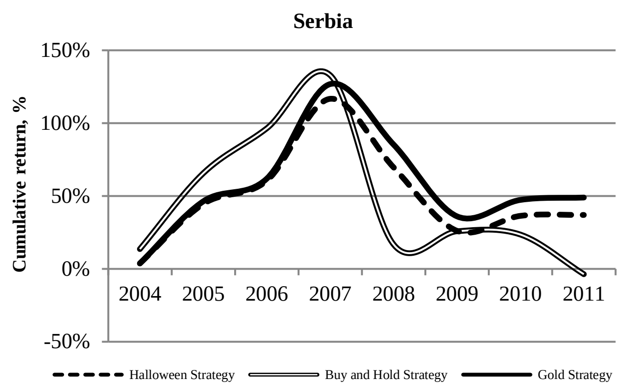
Graph 2 *Cumulative returns of various trading strategies in Ukraine*
Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

In Ukraine the major divergence between the strategies came along in late 2007 when the Gold and Halloween strategies became highly superior comparing to the market. Until 2007, the market portfolio underperformed only a little in comparison to the half-year asset shifting strategies.

In Serbia the data suggests that a great reversal took place in late 2007 as well. Until the moment the market portfolio was much better performing, yet after 2007 the Halloween and Gold strategies became clearly superior.

Similar patterns, yet not so vivid, are present also in Poland, the Czech Republic, and Hungary (Appendix D graphs 4-).

One can clearly see that overall from 2004 till 2011 Halloween and Gold strategies way outperformed buy and hold strategy in the long run in the Countries (with the exception of Poland where only the Gold strategy was more appealing). This can be inferred as evidence that in the long run the trading strategies definitely are more profitable, thus the findings are valuable for long-term investments.



Graph 3 *Cumulative returns of various trading strategies in Serbia*
Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

6. Discussion

The authors found an economically significant Monday effect in Latvia and Croatia, where on average returns on Mondays are much lower than in any other day of the week. However, when testing the phenomenon with another model, the authors rejected the presence of the Monday effect in Croatia, since statistical significance disappeared. This a bit contradicts the work of Sajter and Domagoj (2012) who found the seasonality in the Croatian Stock Market, yet the dummy variable model is still consistent with their finding. Interestingly enough, Klesov (2008) presented mixed results about the Monday effect in Croatia, meaning the dummy regression did not detect the phenomenon, yet the GARCH specification did which is quite opposite to the findings of this study.

In Latvia, the output provided by EGARCH suggested similar results as the initial model; hence, the authors concluded that the Monday effect is present in Latvia, moreover with high economic magnitude (other day returns on average 16 basis points higher than Monday return). These results are inconsistent with previous research done by Avdejev and Kveksas (2007), who found evidence in favour of Monday effect only in Lithuania.

As for the Friday effect, the only country with presence of this seasonality was concluded to be Slovenia. What has to be noted is that this country exhibits this effect in its most pronounced form – Friday returns are statistically and economically significantly positive, while all other day returns are significantly lower. This is consistent with the findings of Klesov (2008) who found some evidence in favour of Friday effect in Slovenia, yet the evidence did not prove to be robust.

The three Baltic countries did not illustrate any signs of the Friday effect just like the work of Klesov (2008). However, Avdejev and Kveksas (2007) claimed the presence of the Friday effect in all three Baltic States with large magnitude. Upon deeper investigation of the latter paper, the authors noted this might have happened due to a misinterpretation of results.

The January effect was detected in Estonia, just like previous studies have suggested, and also in Lithuania, yet less profound, which is probably why only one previous research by Avdejev and Kveksas (2007) detect this phenomenon in Lithuania, and Klesov (2008) did not. As suggested by Al-Rjoub (2004a), January effect should be present in Slovakia; however in this research the authors find no evidence.

Even though explaining the differences in the existing seasonalities is out of the scope of this research, the differences could be explained by macroeconomic factors and country specifics. According to the conclusions of Priestley (1997), seasonalities in equity returns are caused by seasonalities in expected equity returns, which is a result of several risk factors. Seasonalities in January exist because of additional riskiness taking place, since it is a crucial stage of the company business cycle. This influences the current and upcoming performance of the enterprise. Priestley (1997)

The Halloween effect was determined in three countries – Estonia, Serbia and Ukraine, and the results are robust. Once again, this implies that stock markets perform significantly better in the period from November to April as compared to May to October. Why does this effect exist in exactly these countries, yet again the authors wish to point out the macroeconomic factors and differences in expected stock returns, or even winter depression as described by Kamastra *et al* (2003).

Jacobsen and Visaltanachoti (2009) found that the Halloween effect is almost non-existent in the consumer consumption sector, yet huge in production, thus the specifics of the stocks listed in those particular countries could be the reason of detecting the Halloween effect exactly in those countries. Yet, in this research the authors concentrated on the exploitation of this effect rather than explaining it. Hence, the next sections will analyze and interpret the results of previously constructed trading strategies that were aimed at benefiting from the Halloween effect.

The authors found that only three countries out of thirteen studied depicted statistical significance of the superiority of the Halloween and Gold trading strategies. This is contrary to the findings of Bouman and Jacobsen (2002), who studied the developed countries and found the Halloween strategy to be less risky and more profitable than the market portfolio in most of the 17 markets studied.

However, it can still be possible that all the portfolios that had economic superiority and no statistical one in this paper had outperformed the market. The reasoning for it is the higher returns and lower volatility. Hence, the illicit significant alphas could have been disrupted because of a little number of annual observations, unprecedented major capital flows in emerging markets prior to the financial crisis, and a highly volatile period of 2008-2009.

Given the constraint of data the authors of the study did not have a chance to test the exploitability of the Halloween effect in a different time span. However, the authors still applied the strategies to countries where the Halloween effect was not detected. As the authors mentioned in the empirical findings section, portfolios with gold and risk free assets earned more on a risk adjusted basis in Ukraine, Estonia, and the Czech Republic. Nevertheless, one has to treat the results with great precaution, because the positive significant Jensen's alpha in Ukraine and Estonia is just a replica of the Halloween effect dummy regression. Furthermore, if we disregard the latter two countries, we get that one out of eleven countries has a significant alpha at the 10% level, which might mean that it happened by chance.

In terms of economic rationale of the trading strategies, if we assume reasonable transaction costs the magnitude of the Halloween effect in both strategies would outweigh the transaction costs in Ukraine and Estonia. Even though previous literature spoke of reasonable transaction costs at 0.1% of the deal, the authors of this study could claim that costs up 1% could be offset by additional return of the strategy and still be profitable.

7. Conclusion

After reviewing numerous previous studies, extensive data gathering, and assessment of the results, the authors are able to answer the research question of this paper: "*Is it possible to benefit from seasonalities in Central and Eastern Europe?"* Next paragraphs will describe how is doable and what are the limitations of it.

Since the main focus of this research was to construct trading strategies to profitably exploit the Halloween effect, the authors found out that in Ukraine and Estonia this would be most plausible and that the investors should either switch to gold or the so called risk free assets in the period from May to October. This is because the Jensen's alpha in the regression proved to be positive, and economically and statistically significant that would outweigh any reasonable transaction cost of up to 1% of the deal size. In addition, the suggested strategy mean-variance dominates the market portfolio.

Other results, e.g. the superiority of the Gold and Halloween strategies in the Czech Republic, fall into the possible error range of the statistical model. That is why the authors treat the result with caution and do not report it as a possibility of benefiting from the selected strategies. Even after examining the cumulative return graphs, the authors reckon that, for instance, Hungary also exhibits a pattern of higher returns by using the trading strategies, yet the statistical tests proved the seemingly good strategy to happen by chance.

In addition, the presence of the Weekend and the January effects in CEE countries differed to some extent from previous research; hence, the studied phenomenon still does not present uniformed results.

All in all, this study illustrated that investors might benefit from the Halloween effect in some CEE countries, yet why does this phenomenon appear in one country and not in another was out of the scope of the research and might be a challenge for future scholars. Additionally, future work might attain a better dataset which would help to test the profitability of the Halloween and Gold strategies in an out of the sample test.

References

Abraham, A., & Ikenberry, D. L. (1994). The Individual Investor and the Weekend Effect. *Journal of Financial and Quantitative Analysis, 29*(2), 263-277. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/2331225

Ackert, L. F., & Athanassakos, G. (2000). Institutional Investors, Analyst Following, and the January Anomaly. *Journal of Business Finance & Accounting 27*(3), 469-485. doi: 10.1111/1468-5957.00321.

Al-Rjoub, S. A. M. (2004a). Price Pressure around the year-end: Evidence from Emerging Markets. Retrieved from Social Science Research Network, SSRN. Retrieved from http://ssrn.com/abstract=635881

Al-Rjoub, S. A. M. (2004b). The Daily Return Pattern in the Amman Stock Exchange and the Weekend Effect. Retrieved from Social Science Research Network, SSRN. Retrieved from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=484782

Ariel, R. A., (1990). High Stock Returns before Holidays: Existence and Evidence on Possible Causes. *The Journal of Finance, 45(*5), 1611-1626. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Avdejev, A. & Kveksas, M. (2007). *Monthly and Daily Stock Return Anomalies – an Investigation of the Stock Markets in the Baltic States* (Bachelor Thesis). Stockholm School of Economics in Riga.

Baillie, R. T., & DeGennaro, R. P. (1990). Stock Returns and Volatility. *The Journal of Financial and Quantitative Analysis, 25*(2), 203-214. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/2330824

Bell, D., & Levin, E. (1998). What Causes Intra-week Regularities in Stock Returns? Some Evidence from the UK. *Applied Financial Economics*, *8*(4), 353-357. Retrieved from EconPapers. Retrieved from http://econpapers.repec.org

Bloomberg Terminal. (2012). Retrieved January 25, 2012, from http://www.bloomberg.com/professional/software_support/

Bouman, S., & Jacobsen, B. (2002). The Halloween Indicator, "Sell in May and Go Away": Another Puzzle. *The American Economic Review, 92*(5), 1618-1635. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/3083268

Brockman, P., & Michayluk, D. (1998). The Persistent Holiday Effect: Additional Evidence. *Applied Economics Letters, 5*(4), 205-209. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Casado, J., Muga, L., & Santamaria, R. (2011). *The Effect of US Holidays on the European Markets: When the Cat's Away* (Working paper). Retrieved from Social Science Research Network, SSRN. Retrieved November 19, 2011, http://ssrn.com/abstract=1876555

Cervera, A., & Keim, D. B. (Eds.). (2000). *Security Market Imperfections in World Wide Equity Markets*. Cambridge: Press Syndicate of the University of Cambridge. http://books.google.lv/books?id=cDuyJ5tjOxoC&pg=PA512&lpg=PA512&dq=High+Stock+Returns+Before+Holidays:+International+Evidence+and+Additional+Tests.&source=bl&ots=8Av5Kc7NJX&sig=DwWfA1_mrrKLrawjCS5jG2KBb9U&hl=lv&ei=tZ7TTsmHDqaP4gSixtnXDg&sa=X&oi=book_result&ct=result&resnum=2&ved=0CCcQ6AEwAQ#v=onepage&q=High%20Stock%20Returns%20Before%20Holidays%3A%20International%20Evidence%20and%20Additional%20Tests.&f=false

Chan, K. C. (1986). Can tax-loss selling explain the January seasonal in stock returns. *Journal of Finance 41*(5), 1115–1128. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/2328167

Chang, E. C., Pinegarc, J. M., & Ravichandrand, R. (1998). US day-of-the-week effects and asymmetric responses to macroeconomic news. *Journal of Banking & Finance*, *22*(5), 513-534. Retrieved from Science Direct. Retrieved from http://www.sciencedirect.com/science/article/pii/S0378426698000235

Chen, H., Singal, V., & Tech, V. (2003). Do Short Sellers Cause the Weekend Effect? *Journal of Investment Management*, *1*(3), 20-35. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Cross, F. (1973). The behaviour of Stock Prices on Fridays and Mondays. *Financial Analysts Journal*, *29*(6), 67-69. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/4529641

Doeswijk, R. (2009). *The Halloween Effect in US Sectors: Comment* (Working Paper). Retrieved from Social Science Research Network, SSRN. Retrieved November 21, 2011, from http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1456357

Elango, R., & Al Macki, N. (2008). Monday Effect and Stock Return Seasonality: Further Empirical Evidence. *The Business Review, 10*(2), 282-288. Retrieved from Social Science Research Network, SSRN. Retrieved from http://ssrn.com/abstract=1103627

Engle, R. (1982). Autoregressive conditional heteroskedasticity with estimates of variance of U.K. inflation. *Econometria*, *50*(4), 987-1008. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/1912773

Flannery, M., & Protopapadakis, A. (1988). From T-Bills to Common Stocks: Investigating the Generality of Intra-Week Return Seasonality. *Journal of Finance, 43*(2), 431-450. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/2328469

Faff, R. W., & McKenzie, M. D. (2002). The Impact of Stock Index Futures Trading on Daily Returns Seasonality: A Multicountry Study. *The Journal of Business , 75*(1), 95-125. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/10.1086/323506

Fama, E.F. (1970). Efficient Capital Markets: A Review of Theory & Empirical Work. *Journal of Finance, 25*(2), *383-417*. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/2325486

French, K. R. (1980). Stock Retums and the Weekend Effect. *Journal of Financial Economics, 8*(1), 55-69. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Gibbons, M. R., & Hess, P. (1981). Day of the Week Effects in Asset Returns. *Journal of Business, 54*(4), 579-596. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Gultekin, M. N., & Gultekin, N. B. (1983). Stock Market Seasonality: International Evidence. *Journal of Financial Economics, 12*(4), 469-481. Retrieved from Science Direct. Retrieved from http://www.sciencedirect.com/science/article/pii/0304405X83900442

Haug, M., & Hirschey, M. (2006). The January Effect. *Financial Analysts Journal, 62*(5), 78-88. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/4480774

Hirsch, Y. (1986). Don't Sell Stocks on Monday: An Almanac for Traders, Brokers and Stock Market Watchers. New York: Facts on File.

Jacobs, B. I., & Levy K. N. (1988). Calendar Anomalies: Abnormal Returns at Calendar Turning Points. *Financial Analysts Journal*, *44*(6), 28-39. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/4479164

Jacobsen, B., & Visaltanachoti, N. (2009). The Halloween Effect in US Sectors. *Financial Review*, *44*(3), 437-459. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Kamstra, M. J., Kramer, L. A., Levi M. D. (2003). Winter Blues: A SAD Stock Market Cycle. *The American Economic Review*, *93*(1), 324-343. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/3132178

Keim, D. B. (1983). Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics*, *12*(1), 13-32. Retrieved from Science Direct. Retrieved from http://www.sciencedirect.com/science/article/pii/0304405X83900259

Kim, D. (2010). Information Uncertainty Risk and Seasonality in International Stock Markets. *Asia-Pacific Journal of Financial Studies,39*(2), 229-259. Retrieved from Wiley Online Library. Retrieved from http://onlinelibrary.wiley.com/doi/10.1111/j.2041-6156.2010.00011.x/pdf

Kim, D. (2006). On the information uncertainty risk and the January effect. *Journal of Business 79*(4), 2127–2162. Retrieved from Ben-Gurion University of the Negev website. Retrieved from ftp://www.econ.bgu.ac.il/courses/Signaling_in_Financial_Markets/Readings/Articles/2009-01-28%20Anomalies/On%20the%20Information%20Uncertainty%20Risk%20and%20the%20January%20Effect.pdf

Klesov, A. (2008). *Calendar effects on stock market: case of selected CIS and CEE countries* (Master Thesis). National University "Kyiv-Mohyla Academy". Retrieved February 26, 2012, from http://kse.org.ua/uploads/file/Thesis_Mbespalko.pdf

Lakonishok, J. & Smidt, S. (1988) Are Seasonal Anomalies Real? A Ninety-Year Perspective. *The Review of Financial Studies*, *1*(4), pp. 403-425. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/2962097

Lucey, B. M., & Zhao, X. S. (2008). Halloween or January? Yet Another Puzzle. *International Review of Financial Analysis*, *17*(5), 1055-1069. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Maberly, E. D., & Pierce, R. M. (2003). The Halloween Effect and Japanese Equity Prices: Myth or Exploitable Anomaly. *Asia-Pacific Financial Markets, 10*(4), 319-334. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Mathworks. (n/a). *Time Series Modelling*. Retrieved January 25, 2012, from http://www.mathworks.se/help/toolbox/econ/f8-82329.html#f5-18152

Meneu, V. & Padro A. (2004). Pre-holiday effect, large trades and small investor behavior. *Journal of Empirical Finance, 11*(2), 231-246. Retrieved from Science Direct. Retrieved from http://www.sciencedirect.com/science/article/pii/S0927539803000513

Nisser, J. & Valla, T. (2006). Disappearing anomalies: a dynamic analysis of the persistence of anomalies. *Applied Financial Economics, 16*(4), 291-302. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Poterba, J. M., & Weisbenner, S. J. (2001). Capital Gains Tax Rules, Tax-Loss Trading, and Turn-of-the Year Return. *Journal of Finance, 56*(1), 353-368. Retrieved from National Bureau of Economic Research. Retrieved from http://www.nber.org/papers/w6616

Priestly, R. (1997). Seasonality, Stock Returns and the Macroeconomy. *The Economic Journal, 107*(445) 1742-1750. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/2957904

Robinson, J. (2005). Stock Price Behaviour in Emerging Markets: Tests for Weak Form Market Efficiency on the Jamaica Stock Exchange. *Social and Economic Studies, 54*(2), 51-69. Retrieved from JSTOR. Retrieved from http://www.jstor.org

Rozeff, M. S., & Kinney, W. R. (1976). Capital market seasonality: The case of stock returns. *Journal of Financial Economics, 3*(4), 379-402. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Rystrom, D. S., & Benson, E. D. (1989). Investor Psychology and the Day-of-the-Week Effect. *Financial Analysts Journal, 45*(5), 75-78. Retrieved from Business Source Complete, EBSCO. Retrieved from http://search.ebscohost.com

Sajter, D. (2012). *Monday and January Effects on Croatian, Serbian, and Slovenian Stock Exchanges* (Working Paper 569910). Croatian Scientific Bibliography. Retrieved March 17, 2012, from http://bib.irb.hr/prikazi-rad?lang=en&rad=569910

Savva, C.S., Osborn, D.R., Gill, L. (2005). The day of the week effect on stock market volatility using EGARCH framework. Mimeo. Retrieved from University of Manchester. Retrieved November 22, 2011, from http://www.socialsciences.manchester.ac.uk/economics/

Sias, R. W., & Starks, L. T. (1995). The Day-of-the-Week Anomaly: The Role of Institutional Investors. *Financial Analysts Journal*, *51*(3), 58-67. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/4479847

Singh, R. O. (1995). An examination of return predictability on the Trinidad and Tobago Stock Exchange. *Regional Programme of Monetary Studies Conference, 25*. Retrieved Nov 27, 2011, from http://ccmfuwi.org/files/publications/conference/486.pdf

Tangjitprom, N. (2010). Preholiday Returns and Volatility in Thai stock market. *Asian Journal of Finance & Accounting, 2*(2), 41-54. Retrieved from Macrothink Institute. Retrieved from http://www.macrothink.org/journal/

Thomson Reuters Datastream. (2012). Retrieved January 25, 2012, from Riga Business School.

Urrutia, J. L., & Vu, J. (2006). Empirical Evidence of Nonlinearity and Chaos in the Returns of American Depository Receipts. *Quarterly Journal of Business and Economics 45*(1/2), 15-30. Retrieved from JSTOR. Retrieved from http://www.jstor.org/stable/40473412

Appendix 1.

Table 1. *List of Indices and their respective market*

Country	Index
Bulgaria	DJTM BULGARIA $
Croatia	MXCR index
Czech Republic	TR CZECH REPUBLIC L
Estonia	OMX TALINN
Hungary	ACHUN Index
Latvia	OMX RIGA
Lithuania	OMX VILNIUS
Poland	WARSAW GENERAL INDEX
Romania	S&P ROMANIA BMI
Serbia	BELEXline Index
Slovakia	SKSM Index
Slovenia	MSCI SLOVENIA
Ukraine	S&P UKRAINE BMI

Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

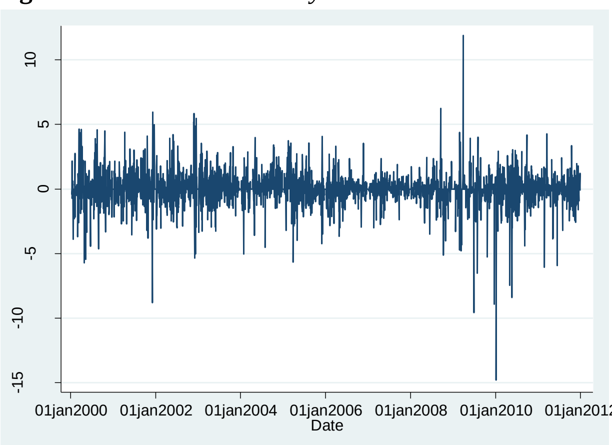
Appendix 2.

Table 2. *Statistical characteristics of daily returns*

Country	N	Mean (%)	St. dev. (%)	Skewness	Kurtosis
Bulgaria	1322	0.1140	6.2653	32.0912	1120.18
Croatia	2499	0.0056	1.4569	-0.0502	11.61
Czech Republic	3147	0.0334	1.5679	-0.4828	14.64
Estonia	3113	0.0422	1.2204	0.1112	10.58
Hungary	1403	-0.0292	2.1865	0.0258	9.05
Latvia	3147	0.0412	1.5736	-0.6105	16.99
Lithuania	3147	0.0361	1.2121	-0.4814	25.50
Poland	3147	0.0233	1.3783	-0.3194	6.06
Romania	3147	0.0558	2.0639	0.1238	61.15
Serbia	1889	-0.0019	1.0476	0.2535	14.18
Slovakia	3124	0.0322	1.2185	-0.9500	20.43
Slovenia	2518	0.0107	1.3622	0.2365	14.87
Ukraine	3147	0.0692	2.3170	6.8493	159.76

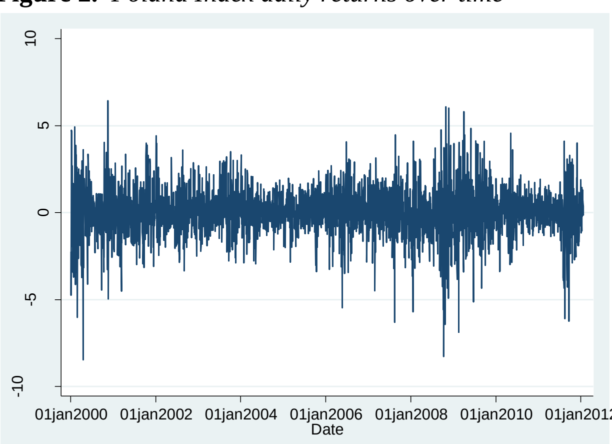
Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Figure 1. *Slovakia Index daily returns over time*



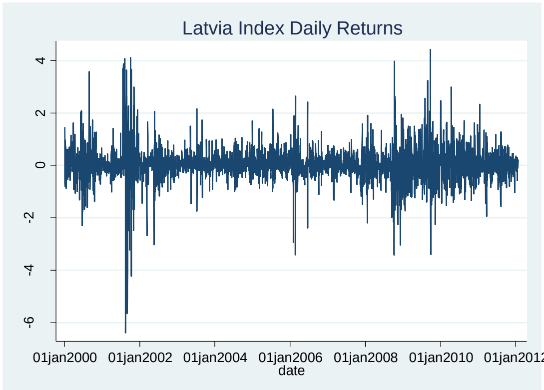
Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Figure 2. *Poland Index daily returns over time*



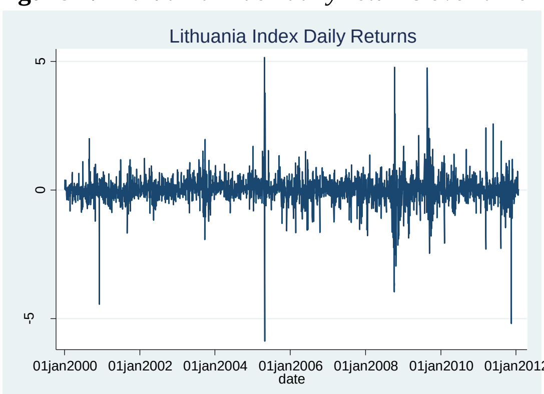
Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Figure 3. *Latvia Index daily returns over time*



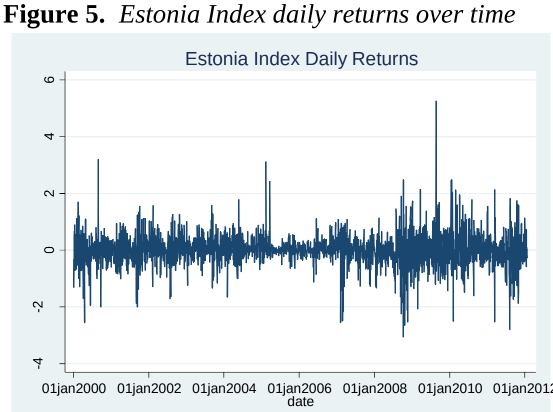
Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Figure 4. *Lithuania Index daily returns over time*



Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Figure 5. *Estonia Index daily returns over time*



Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 3. *Weekday average daily return statistics for CEE countries*

	Bulgaria	Croatia	Czech	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Serbia	Slovakia	Slovenia	Ukraine
Monday	-0.2110	-0.1207	0.0940	0.0145	0.1495	-0.0890	-0.0072	0.0179	0.0316	-0.0235	-0.0011	-0.0861	-0.0452
Tuesday	-0.1757	0.0981	-0.0156	0.0164	-0.0291	-0.0028	-0.0020	-0.0048	0.0218	-0.1140	-0.0244	-0.1334	0.0891
Wednesday	0.0679	0.0509	-0.0184	0.0729	-0.0064	0.0704	0.0313	-0.0175	0.1114	-0.0213	0.0473	0.0058	0.0813
Thursday	0.8217	-0.0381	0.0954	0.0388	-0.1522	0.1150	0.0646	0.0332	-0.0159	0.0720	0.0713	0.0345	-0.0659
Friday	0.0686	0.0378	0.0114	0.0690	-0.1074	0.1125	0.0938	0.0879	0.1302	0.0770	0.0683	0.2329	0.2867

Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 4. *Month of the year average daily returns for CEE countries*

	Bulgaria	Croatia	Czech	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Serbia	Slovakia	Slovenia	Ukraine
January	-0.2931	0.0692	0.0936	0.2675	-0.1147	0.0890	0.1753	0.0272	0.1082	0.1598	-0.0608	0.0730	0.3146
February	0.1823	-0.0219	-0.0144	0.0187	-0.1797	-0.1154	-0.0261	-0.0489	0.0409	0.0714	0.0840	-0.1245	0.3025
March	0.0579	0.0181	0.0930	0.1045	0.1740	0.0704	0.0728	0.1017	-0.0165	0.1160	0.0915	-0.0347	0.1276
April	0.1261	0.0217	0.1450	0.0286	0.3186	0.1316	0.0300	0.1167	0.1823	0.0837	-0.0266	0.0952	0.1493
May	0.0815	0.0161	-0.0096	-0.0309	0.0187	-0.1103	0.0205	0.0208	0.0513	0.1486	-0.0557	0.1181	0.0231
June	-0.1553	0.0428	-0.0738	-0.0512	-0.1240	0.1377	0.0096	-0.0782	-0.0189	-0.0741	-0.0178	-0.0153	-0.0776
July	0.0141	0.0262	0.1182	-0.0218	0.1915	0.2069	0.0657	0.1134	0.1709	-0.1009	0.0807	0.1045	-0.1274
August	0.1453	0.0357	0.0047	0.1490	-0.1378	0.1838	0.1757	0.0055	0.0813	0.0544	0.1519	0.0440	-0.0971
September	1.9759	0.0350	-0.0846	-0.0376	-0.1552	-0.0893	0.0802	-0.1167	-0.0516	-0.1105	0.0661	-0.0521	-0.1843
October	-0.4870	-0.1229	0.0112	-0.0862	-0.1899	-0.0239	-0.1474	0.0527	-0.0218	-0.1606	-0.0486	0.0558	-0.0587
November	-0.2134	-0.1239	-0.0570	0.0282	-0.1601	-0.0277	-0.0823	-0.0132	0.0306	-0.2361	0.0917	-0.1118	0.0217
December	0.0251	0.0735	0.1617	0.1121	0.0647	0.0248	0.0409	0.0876	0.1076	0.0657	0.0313	-0.0349	0.4320

Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Appendix 3.

Table 5. *Monday effect regression output.*

	Bulgaria	Croatia	Czech	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Serbia	Slovakia	Slovenia	Ukraine
Tuesday	0.0353*	**0.2188****	-0.1096	0.0019	-0.1786	**0.0862**	0.0052	-0.0227	-0.0098	-0.0905	-0.0233	-0.0473	0.1343
Wednesday	0.2789	**0.1716***	-0.1124	0.0584	-0.1559	**0.1594***	0.0385	-0.0354	0.0798	0.0022	0.0484	0.0919	0.1265
Thursday	1.0327	**0.0826**	0.0014	0.0243	-0.3017	**0.2040****	0.0718	0.0153	-0.0475	0.0955	0.0724	0.1206	-0.0207
Friday	0.2796*	**0.1585***	-0.0826	0.0545	-0.2569	**0.2016****	0.1009	0.0700	0.0986	0.1005	0.0694	0.3189***	0.3318**
Constant	-0.2110*	**-0.1207***	0.0940	0.0145	0.1495	**-0.0890**	-0.0072	0.0179	0.0316	-0.0235	-0.0011	-0.0861	-0.0452

Note: the figures presented in table 5 are coefficients of the respective regression dummies that represent the difference of the dummy from the constant. The constant is the average daily return for Monday in the period under study. The asterisks indicate the level of statistical significance: *, **, *** stand for 10%, 5%, and 1% level of significance, respectively. Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 6. *Friday effect regression output.*

	Bulgaria	Croatia	Czech	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Serbia	Slovakia	Slovenia	Ukraine
Monday	-0.2796*	-0.1585*	0.0827	-0.0545	0.2569	-0.2016**	-0.1009	-0.0700	-0.0986	-0.1005	-0.0694	**-0.3189*****	-0.3318**
Tuesday	-0.2443*	0.0603	-0.0269	-0.0527	0.0783	-0.1154	-0.0958	-0.0927	-0.1083	-0.1910**	-0.0927	**-0.3663*****	-0.1975
Wednesday	-0.0007	0.0131	-0.0298	0.0038	0.1009	-0.0422	-0.0625	-0.1054	-0.0188	-0.0983	-0.0210	**-0.2270*****	-0.2053
Thursday	0.7531	-0.0759	0.0841	-0.0303	-0.0448	0.0025	-0.0292	-0.0547	-0.1461	-0.0050	0.0030	**-0.1984****	-0.3525**
Constant	0.0686	0.0378	0.0114	0.0690	-0.1074	0.1125*	0.0938**	0.0879*	0.1302	0.0770	0.0683	**0.2329*****	0.2867**

Note: the figures presented in table 6 are coefficients of the respective regression dummies that represent the difference of the dummy from the constant. The constant is the average daily return for Fridays in the period under study. The asterisks indicate the level of statistical significance: *, **, *** stand for 10%, 5%, and 1% level of significance, respectively. Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 7. *January effect regression output.*

	Bulgaria	Croatia	Czech	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Serbia	Slovakia	Slovenia	Ukraine
February	0.4754**	-0.0911	-0.1080	**-0.2488****	-0.0650	-0.2044*	**-0.2014****	-0.0761	-0.0673	-0.0884	0.1448	-0.1975*	-0.0121
March	0.3510*	-0.0511	-0.0006	**-0.1630**	0.2887	-0.0186	**-0.1025**	0.0745	-0.1247	-0.0438	0.1523	-0.1077	-0.1870
April	0.4192*	-0.0475	0.0514	**-0.2389****	0.4333*	0.0426	**-0.1453**	0.0895	0.0741	-0.0761	0.0342	0.0222	-0.1653
May	0.3746*	-0.0531	-0.1032	**-0.2984*****	0.1334	-0.1993*	**-0.1548***	-0.0064	-0.0569	-0.0112	0.0051	0.0451	-0.2915
June	0.1378	-0.0264	-0.1674	**-0.3187*****	-0.0093	0.0487	**-0.1657****	-0.1054	-0.1271	-0.2339**	0.0430	-0.0883	-0.3922**
July	0.3072	-0.0430	0.0246	**-0.2893*****	0.3062	0.1179	**-0.1096**	0.0862	0.0627	-0.2607***	0.1415	0.03146	-0.4420**
August	0.4384**	-0.0335	-0.0889	**-0.1185**	-0.0231	0.0948	**0.0004**	-0.0217	-0.0269	-0.1054	0.2127**	-0.0290	-0.4117**
September	2.269	-0.0342	-0.1782	**-0.3051*****	-0.0405	-0.1783	**-0.0951**	-0.1439	-0.1598	-0.2703***	0.1269	-0.1251	-0.4989***
October	-0.1939	-0.1921	-0.0824	**-0.3537*****	-0.0752	-0.1129	**-0.3227*****	0.0255	-0.1300	-0.3204**	0.0122	-0.0172	-0.3733*
November	0.0797	-0.1931	-0.1506	**-0.2393****	-0.0454	-0.1167	**-0.2576*****	-0.0404	-0.0776	-0.3959***	0.1525	-0.1848	-0.2929*
December	0.3182	0.0043	0.0681	**-0.1554***	0.1794	-0.0642	**-0.1344***	0.0604	-0.0006	-0.0941	0.0921	-0.1079	0.1174
Constant	-0.2931*	0.0692	0.0936	**0.2675***	-0.1147	0.0890	**0.1753*****	0.0272	0.1082	0.1598***	-0.0608	0.0730	0.3146**

Note: the figures presented in table 7 are coefficients of the respective regression dummies that represent the difference of the dummy from the constant. The constant is the average monthly return for Januaries in the period under study. The asterisks indicate the level of statistical significance: *, **, *** stand for 10%, 5%, and 1% level of significance, respectively. Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 8. *Halloween effect regression output.*

	Bulgaria	Croatia	Czech	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Serbia	Slovakia	Slovenia	Ukraine
Winter	-0.2867	0.0011	0.0770	**0.1105****	0.0889	-0.0198	0.0041	0.0458	0.0400	**0.0802***	0.0055	-0.0638	**0.3121*****
Constant	0.2585	0.0051	-0.0050	**-0.0131**	-0.0731	0.0511	0.0341	0.0005	0.0359	**-0.0423**	0.0296	0.0418	**-0.0865***

Note: the figures presented in table 8 are coefficients of the respective regression dummies that represent the difference of the dummy from the constant. The constant is the average daily return for the May-October (summer) periods in the period under study. The asterisks indicate the level of statistical significance: *, **, *** stand for 10%, 5%, and 1% level of significance, respectively. Source: created by the Authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 9. *Adjusted Halloween effect regression output.*

	Bulgaria	Croatia	Czech	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Serbia	Slovakia	Slovenia	Ukraine
Winter	-0.2242	-0.0112	0.0723	**0.0729***	0.1136	-0.0325	-0.0260	0.0500	0.0329	0.0568	0.0247	-0.0841	**0.2926*****
January	-0.5515	0.0641	0.0986	**0.2806*****	-0.0416	0.0379	0.1412**	0.0267	0.0724	0.2020***	-0.0903	0.0312	**0.4011*****
Constant	0.2584	0.0051	-0.0050	**-0.0131**	-0.0731	0.0511	0.0341	0.0005	0.0359	-0.0423	0.0296	0.0418	**-0.0865***

Note: the figures presented in table 9 are coefficients of the respective regression dummies that represent the difference of the dummy from the constant. The constant is the average daily return for the May-October (summer) periods in the period under study. The asterisks indicate the level of statistical significance: *, **, *** stand for 10%, 5%, and 1% level of significance, respectively. Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 10. *Comparison of different trading strategy returns and standard deviations across countries.*

	Buy and Hold Strategy		Halloween Strategy		Gold Strategy	
Country	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**	**Mean**	**Standard Deviation**
Bulgaria	30.15%	141.04%	-3.80%	25.96%	-2.01%	25.92%
Croatia	1.40%	39.71%	0.76%	22.89%	1.25%	23.77%
Czech Republic	**8.68%**	**30.41%**	**9.42%**	**13.82%**	**10.11%**	**14.08%**
Estonia	**10.66%**	**42.82%**	**12.44%**	**24.10%**	**13.50%**	**24.28%**
Hungary	**-6.84%**	**47.68%**	**1.81%**	**15.04%**	**3.07%**	**14.56%**
Latvia	10.56%	36.54%	3.87%	24.14%	4.30%	24.70%
Lithuania	9.12%	47.65%	4.69%	24.50%	5.38%	25.12%
Poland	**5.70%**	**32.80%**	**5.66%**	**14.18%**	**6.26%**	**13.62%**
Romania	14.55%	47.16%	9.89%	23.12%	10.69%	23.59%
Serbia	**-0.46%**	**52.79%**	**4.62%**	**36.14%**	**6.12%**	**38.31%**
Slovakia	8.40%	24.96%	4.53%	11.40%	4.55%	12.12%
Slovenia	3.94%	45.49%	-2.02%	24.55%	-1.10%	23.49%

Ukraine	**17.57%**	**62.17%**	**29.17%**	**40.41%**	**30.42%**	**41.93%**

Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 11. *Halloween strategy estimation results.*

Halloween Strategy		
Country	**α**	**β**
Bulgaria	-0.1124	0.1745***
Croatia	-0.0118	0.5730***
Czech Republic	**0.0421***	**0.3934*****
Estonia	**0.0557***	**0.5073*****
Hungary	0.0148	0.2488*
Latvia	-0.0372	0.6098***
Lithuania	-0.0085	0.4188***
Poland	0.0176	0.3450***
Romania	0.0273	0.3630***
Serbia	0.0357	0.5013***
Slovakia	-0.0315	0.3478***
Slovenia	**-0.05288***	**0.5189*****
Ukraine	**0.1974****	**0.4429****

Note: α denotes the additional return on a market risk adjusted basis, measured as annual returns. The β denotes the Halloween strategy portfolio sensitivity to market movements. The asterisks indicate the level of statistical significance: *, **, *** stand for 10%, 5%, and 1% level of significance, respectively.

Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Table 12. *Gold strategy estimation results.*

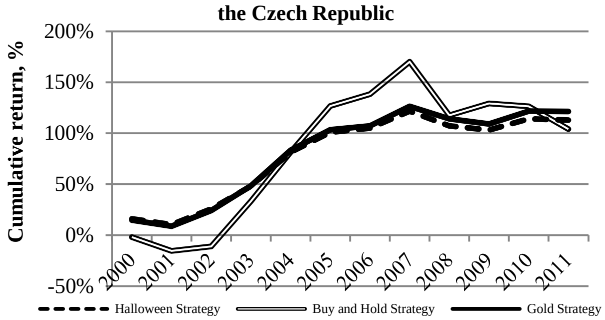
Gold Strategy		
Country	**α**	**β**
Bulgaria	-0.0938	0.1718***
Croatia	-0.0074	0.5267***
Czech Republic	**0.0478***	**0.3969*****
Estonia	**0.0667***	**0.5027*****
Hungary	0.0257	0.2311
Latvia	-0.0327	0.6076***
Lithuania	-0.0016	0.4197***
Poland	0.0241	0.3278***
Romania	0.0382	0.3379
Serbia	0.0502	0.4839***
Slovakia	-0.0039	0.3640***
Slovenia	-0.0433	0.4913***
Ukraine	**0.2100****	**0.4425****

Note: α denotes the additional return on a market risk adjusted basis, measured as annual returns. The β denotes the Gold strategy portfolio sensitivity to market movements. The asterisks indicate the level of statistical significance: *, **, *** stand for 10%, 5%, and 1% level of significance, respectively.

Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

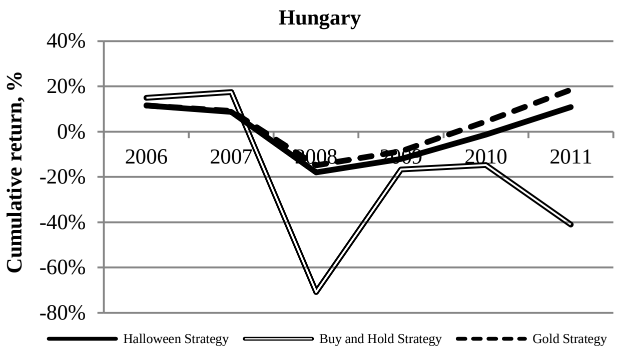
Appendix 4.

Graph 4. *Cumulative returns of various trading strategies in the Czech Republic*



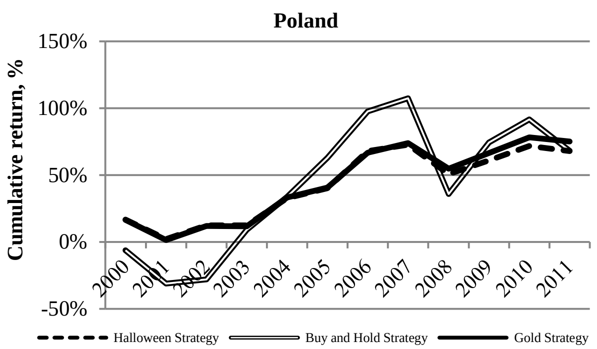
Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Graph 5. *Cumulative returns of various trading strategies in Hungary*



Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)

Graph 6. *Cumulative returns of various trading strategies in Poland*



Source: created by the authors, based on data from Thomson Reuters and Bloomberg Terminal (2012)