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BACHELOR THESIS

Seasonal Effects on Stock Markets in Europe

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature.

The author hereby declares that this thesis has not been used to obtain another university degree.

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Prague, May 11, 2016

Signature

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Abstract

This thesis researches the problem of stock market efficiency and market anomalies. Specifically, we look on European stock markets and possible presence of four seasonal effects—January, Halloween, Turn-of-the-month and Monday effects. These seasonal anomalies imply that returns for specific period are unusually higher or lower than returns for the rest of the time, which presents a challenge for the Efficient Market Hypothesis. The empirical side of this problem is the possible opportunity for excessive profit from trading on stock markets that could be based on the seasonal anomalies. Firstly, we summarize previous research in the field and attempts of explanation of individual effects. Further, we present the tools needed for our analysis—Ordinary Least Squares regression with dummy variables and few extensions. Data used for the analysis consists of 32 European stock indices. The actual analysis is performed as a comparison of returns on stock for certain specified periods. The evidence on January and Monday effects is found not strong enough to confirm the presence of such anomalies. On the other side, there is enough significant evidence on the presence of Halloween and Turn-of-the-month effects. Moreover, we are unable to explain the Halloween effect as manifestation of January effect.

Bibliographic Record

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Abstrakt

Tato práce se zaměřuje na efektivitu akciových trhů a tržní anomálie. Konkrétně zkoumá možnou přítomnost čtyř sezónních efektů—Lednového efektu, „Halloween“ efektu, efektu Přelomu měsíce a Pondělního efektu—na evropských akciových trzích. Podle těchto sezónností by měly být výnosy z akcií v jistých obdobích neobvykle vysoké nebo nízké v porovnání s ostatními obdobími. Přítomnost těchto sezónních efektů představuje jistou výzvu pro Hypotézu efektivních trhů. Praktickou stránkou této problematiky je případná příležitost pro nadměrné zisky z obchodu s akciemi, jež tyto anomálie mohou představovat. Prvně shrneme předchozí výzkum v této oblasti a pokusy o vysvětlení jednotlivých efektů. Dále představíme vhodné nástroje—regrese pomocí metody nejmenších čtverců s binárními proměnnými a případnou nadstavbou. Data použitá k analýze se skládají z 32 evropských akciových indexů. Samotná analýza je provedena porovnáním výnosů z akcií pro konkrétní období. Pro Lednový a Pondělní efekt však neshledáváme výsledky dostatečně přesvědčivé pro tvrzení o přítomnosti těchto anomálií. Na druhé straně jsme ale byli schopni nalézt dostatek důkazů k potvrzení přítomnosti „Halloween“ efektu a efektu Přelomu měsíce. „Halloween“ efekt nejsme ale schopni náležitě vysvětlit jakožto jeden z projevů Lednového efektu.

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Bachelor Thesis Proposal

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Proposed topic	Seasonal Effects on Stock Markets in Europe

Topic characteristics Efficient market theory claims that there should not be any predictable and exploitable inefficiency in the market. But the theory comes under a close scrutiny since there is empirical evidence of seasonal anomalies on the stock market. Due to the theory, the anomaly should be arbitraged right after its discovery if it is possible. And it is indeed true in some cases, some anomalies even reverse themselves after time. This thesis will focus mainly on the question of stock markets and its anomalies like January effect, so-called Halloween effect also known as a saying "Sell in May, go away", Monday effect and the Turn-of-the-month effect in Europe. But there are of course many other seasonal anomalies on the stock markets, Pre-Holiday or Intra-month effects being one of them, just to mention some examples. The January effect was among others described by Rozeff & Kinney (1976) and the idea behind it is that the returns on stock are significantly higher than in other months in the year. But even after its discovery it is recorded that this effect is ongoing. The Halloween effect, sometimes known as the old stock market adage "Sell in May, go away" was described by Bouman & Jacobsen (2002) and they claim that the returns on stock are unusually higher from November through April than the rest of the year. It is interesting to see that the adage can be tracked down even to the 1930s (Financial Times 10/5/1935) and yet the effect still can be found according to Bouman & Jacobsen (2002) in data from years 1970-1998. They even propose a trading strategy based on their findings. Some academics provide simple explanation for this effect. They claim that the Halloween effect is just January effect in disguise. Hence there arise another question for our thesis and that is the relationship between these two effects. Monday effect is somewhat special among other anomalies. First, it was described as significantly negative returns on Monday, for example in a paper by French (1980). Later this effect evolved and now we can see positive returns on Mondays, but still significantly lower than returns for the rest of week, at least for some stock indices in the US (Mehdian & Perry 2001). Last but not least, we will examine the Turn-of-the-month effect for Europe. The principle of this phenomenon is that returns on stock are higher in period from the last day of a first month to the third day of the second month. This effect was described by Cadsby & Ratner (1992) among others and they found this effect in 6 out of 10 countries they examined. A goal of the thesis will be to explore if these calendar effects can still be found in Europe using up to date available data from European stock markets.

Hypotheses

1. January effect can be found in European stock markets
2. Halloween effect can be found in European stock markets
3. Halloween effect can be explained by high January returns
4. There is evidence of Monday effect in European stock markets
5. There is evidence of Turn-of-the-month effect in European stock markets

Methodology Econometric analysis of monthly or daily data like European stock indices (e.g. DAX, FTSE 100 or CAC 40) mainly through the OLS regression with dummy variables and related statistical tests. We will add robust regressions if the OLS will prove to be problematic.

Outline

1. Introduction
2. Efficient Markets, discovered seasonal effects and possible explanations
3. Data and methodology for the analysis
4. Seasonal effects and our analysis
    (a) January effect

(b) Halloween effect

(c) Monday effect

(d) Turn-of-the-month effect

(e) Interpretation of the results

(f) Efficient Markets theory revisited

5. Conclusion

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Chapter 1

Introduction

One of the key assumptions of economics as a science is rationality of all participating members. Efficient Market Hypothesis originates from this rationality. Fama (1970) defines the efficient market in the following way: "*A market in which prices 'fully reflect' available information is called 'efficient'.*" The definition of "available information" set aside for now, this claim suggests that trading on stock market would present "a fair game"(Fama 1970). Although seasonal patterns violate this statement, evidence supporting the existence of seasonal anomalies was found by studies such as Rozeff & Kinney (1976), Ariel (1987) or French (1980). At this moment, the efficiency of markets should come into play and the market participants adjust their expectations. This would results into markets that "fully reflect" all available information. But studies from Haug & Hirschey (2006), Sun & Tong (2002) and Haggard & Witte (2010) were able to confirm the presence of seasonal effects on modern stock markets as well. According to Efficient Market Hypothesis, the persistence of seasonal effects should not be possible since we would be able to predict future stock returns on the basis of analysis of past prices.

Although the assumption of the Efficient Market Hypothesis including no transaction costs, costless availability of all relevant information to all traders and agreement among traders on consequences of new information on stock, might seem a little unrealistic, we would expect participants on financial markets to be rational enough not to allow some simple seasonal pattern to persist and repeatedly create opportunities for excessive financial profit. Such an opportunity was presented by Bouman & Jacobsen (2002) with profitable trading strategy based on Halloween effect.

Hence, the goal of this thesis is to present a suitable tool to test for the presence of certain seasonal effects. Such a suitable tool for our analysis proves to be Ordinary Least Squares (henceforth OLS) regression with the addition of related statistical tests and few extensions. The OLS is both consistent with previous research in this field, e.g. Mehdian & Perry (2001) or Kunkel *et al.* (2003) and adequate for this kind of analysis. Dummy variables are appropriate instrument to help us compare returns in different seasons and thus to confirm or disprove the presence of the seasonal anomalies on European stock markets. Important aspect of this work is the updated dataset of 32 European stock markets.

The structure is as follows, Chapter 2 covers basic definitions of the Efficient Market Hypothesis and pursues previous research in the field of seasonal effects. In Chapter 3 the basic methodology is introduced with short description of used dataset. The results of our performed analysis are presented and interpreted in Chapter 4. Chapter 5 concludes our findings.

Chapter 2

Efficient Markets and Seasonal Effects

2.1 Efficient Markets

Efficient Market Hypothesis claims that the efficient markets absorb all available information and react almost immediately. It should be impossible to beat the stock market with some rule or to find any prevailing anomalies that could offer us opportunities for extraordinary profits. These opportunities should be exploited right after their discovery. Despite this hypothesis there were found persistent seasonal effects on world equity markets, e.g. Rozeff & Kinney (1976), Bouman & Jacobsen (2002) or Agrawal & Tandon (1994). This is the first main challenge for this hypothesis. The other interesting fact is that studies like Bouman & Jacobsen (2002) even propose potential trading strategies that prove to be successful based on the anomalies. That should not be possible based on efficient markets.

It should be noted that the presence of some seasonal patterns on stock market might not immediately mean the existence of the possibility to exploit them. Despite some proposed trading strategies, it is polemized upon the possibility of beating the stock market with trading rule based upon these anomalies. Transaction costs and other costs connected to the trading on stock exchange might effectively disallow any opportunity for financial profits that the seasonal effects might present. As Richard Roll, American financial economist, stated: *"After spending 25 years looking at particular allegations about market inefficiencies, and 10 years attempting to exploit them as a practicing money manager... by actually trading significant amounts of money according to a* *trading rules suggested by the 'inefficiencies'... I have never yet found one that worked in practice, in the sense that it returned more after cost than a buy-and-hold strategy".* In this context, Roll (1994) namely mentioned January and day-of-the-week effects and stated that he became "personally suspicious" of many academic studies on anomalies of liquid bonds and stock markets although these "inefficiencies" are surprisingly strong in empirical work.

The term "efficient" markets marks the stock markets where the prices "fully reflect" all available information about the stock. Fama (1970) stated three sufficient conditions for efficient stock markets, specifically: no transaction costs, costless availability of all relevant information to all traders and agreement among traders on consequences of concrete information on specific stock. It is important to stress that, according to Fama (1970), these conditions are sufficient and not necessary for markets to be efficient. Despite failing to meet some or all of the conditions, the market may still be efficient. But failure of these conditions pose a threat towards the efficiency of the markets. But in the case of stock markets, conditions like no transaction costs or overall agreement on precise effect of some information are hard to meet. Mainly, the interpretation of some information concerning specific stock will always be different for every trader since they have different knowledge and experience.

Fama (1970) also distinguished three states of efficient markets: weak, semi-strong and strong. Weak form considers the available information to be past stock prices. No prediction of future prices should be made or excess profits earned thanks to analysis of past prices. In semi-strong form, the information is represented by publicly available information. Strong form claims that the market should behave efficiently when the considered set of information are also private, inside information. In this thesis, we will take on the weak form of market efficiency proposed by Fama (1970) since we use only historical values of stock indexes in our analysis.

The aim of this text is primarily to test whether the seasonal effects are still present on European stock markets, decades after the discovery of these anomalies.

2.2 Seasonal Effects

Seasonality in general is some kind of pattern or fluctuation repeated over known time period. Industries like construction, hospitality, agriculture or tourism provide fine examples of seasonality. Several studies in the past found evidence that the behaviour of prices on stock markets are liable to the seasonality as well (Agrawal & Tandon 1994). Whether it is intra-day seasonality (Harris 1986)—notable importance of the first 45 minutes of trading of the day, daily seasonality—significantly negative returns on Mondays (French 1980) or monthly seasonality—high January returns for small firms in comparison with other months (Haug & Hirschey 2006). The issue with seasonality on the stock markets is its presence in the first place. It is indeed possible that not all agents on the market behave rationally. But the more important and serious issue with seasonality is the persistence of those anomalies. Since efficient markets should "fully reflect" the available information (in this case all historical prices), the repeating presence of seasonal effects should not be possible. Clearly, some repeating seasonal changes can influence the price of equity, but after its discovery, such seasonality should be incorporated in the expectations of every agent on the market. Hence this information would be used up by the participants of the market and therefore such anomaly should eventually disappear.

Further, if we adopt the intuition that higher risk should lead to higher return, we should make one more important assumption with respect to seasonal effects and market efficiency. We should assume the same rate of risk for every season (month, day, etc.), because if risk, say, for January would be higher than for other months, the expected returns would be higher as well.

2.2.1 January Effect

January effect is defined as unusually high returns on equity in January in comparison with other months. The interesting question is why are the returns higher in certain period of the year and what causes this anomaly to be in January.

The study of Rozeff & Kinney (1976) was among the first ones to describe the January effect. They suggested that market seasonality is a strong effect present on the U.S. stock market and also added that stock returns are unusually high in January in comparison with the rest of the year.

Following research does confirm such findings, for example Roll (1983) and Keim (1983) agree with Rozeff & Kinney (1976) about the presence of January effect. Both of these studies also link this seasonality mainly to the shares of smaller firms. In general, such link is explained by higher volatility and lower liquidity of such stock. Keim (1983) found evidence on such link in the first part of the month in his data from U.S. market. According to this study, smaller firms have higher returns in January than their larger counterparts and denotes such event as a "size premium". Such premium is therefore risk-related and can be excepted as partial explanation of such evidence.

The phenomena is also found by Gultekin & Gultekin (1983) in most of the 17 countries they examined. They argue that the presence of January effect might be partially explained by tax-loss selling hypothesis. However this hypothesis is not suitable for some cases, e.g. Australia, where the tax year does not begin in January.

Moller & Zilca (2008) study is one of the more up-to-date ones which found out that higher returns for the beginning of January are followed by mean-reverting component for the rest of the month.

The interesting part of this effect is the arising conflict with Efficient Markets Hypothesis. This proposition states that all available information should be reflected on the stock prices. The important question then comes up, how is it possible that researchers as Roll (1983) or Gultekin & Gultekin (1983) found consistent January effect on diverse stock markets.

One possible explanation is the tax selling hypothesis. It suggests that some agents on the market are selling the "losing stock" before the end of the year to realize the loss before the end of the year and hence lower their basis for tax. It also proposes holding the rising stock in order to reduce the stream of payments on capital gains. This proposition then assumes partial repurchase of the stock again in January. This behaviour corresponds with the optimal trading policy stated by Constantinides (1984). Some evidence in favour of the hypothesis provides the study from Poterba & Weisbenner (2001). They claimed that their results *"provide some support for the view year-end, tax motivated trading by individual investors contributes to turn-of-the-year anomalies"*. It should be stressed out that the research was concerned with individual investors because their motivation related to taxes is more significant. Poterba & Weisbenner (2001) followed with a question on institutional investors and their contribution to the second possible explanation raised, the "window-dressing". Arguments made against the tax-selling option should be noted as well, e.g. why was the effect observable in Canada, when there was no capital gains tax at that time or the presence of the effect on Great Britains' and Australian markets when their tax year does not begin in January (Thaler 1987). Also, Haug & Hirschey (2006) found the January effect on U.S. market to be consistent over time and not affected by the Tax Reform Act in 1986. After the reform, the losses accrued by institutional investors in the last two months of the year were carried over to the next financial year. Thus, the incentive built in the tax-loss selling hypothesis should disappear. It is interesting to see that Haug & Hirschey (2006) found the effect to be persistent even in the period after 1986.

Other explanation provides so-called "window dressing", which is driven mainly by institutional investors (Moller & Zilca 2008). According to this possible explanation, the portfolio managers sell some undesirable, underperforming stock before the end of the year to present respectable portfolio to the investors, only to buy back the same stock in the beginning of the following year. Therefore, drop in stock prices in December would be followed by increase in the prices in January.

Overall review of previous research

Overall, the January effect is more often found on smaller firms as far as research on U.S. stock market data goes. Roll (1983) and Keim (1983) are fine examples of that. In the more recent analysis of U.S. markets, the equal-weighted indexes show better results in the favour of the January phenomenon in comparison with value-weighted indexes. Presented for example by Moller & Zilca (2008) or Haug & Hirschey (2006), these results go hand in hand with the January effect being more evident in smaller firms as suggested in earlier research.

As far as the international evidence goes, there is no clear agreement on the evidence of this seasonal pattern. Gultekin & Gultekin (1983) and Agrawal & Tandon (1994) do find evidence on this effect in their international research (17 and 18 researched countries, respectively), whereas Giovanis (2009) rejects the possibility of presence of January effect on the basis of his global research on 55 stock markets.

2.2.2 Halloween effect

Halloween effect is also known as the adage "Sell in May, go away". Similarly to the January effect, Halloween effect suggests higher returns on stock, this time during November through April in comparison with the rest of the year. The saying "Sell in May, go away" can be tracked down even to the 1930s

(Financial Times in 1935)[1], hence it is interesting to note that this effect was found by Dumitriu *et al.* (2012) on data for period from 2000 to 2006. On the other hand they compare this period with data from 2007 to 2011 where no such effect could be found. They even found that on certain developed markets the anomaly tends to reverse itself.

Bouman & Jacobsen (2002) researched this hypothesis on data from 37 countries around the world during the period 1970 to 1998. They found the effect statistically significant in 20 out of the 37 countries at 10-percent level with the effect being significant at 1-percent level in 10 of those countries. This study even proposed a trading strategy based on their findings. This "Halloween strategy" recommends buying a portfolio at the end of October and selling it at the end of May. During the period from end of the October through the end of April, this strategy proposes buying and holding risk-free short-term Treasury bonds. This study compares this strategy with simple "Buy-and-hold strategy" and the results show that the first strategy outperforms Buy-and-hold strategy on 35 of the 37 researched countries. Their results proved to be consistent even after implementing transaction costs.

Recent study from Dichtl & Drobetz (2014) confirmed the existence of Halloween effect in their study on 5 leading stock indexes (S&P 500, CAC 40, DAX 30, FTSE 100 and Euro Stoxx 50), but unlike the Bouman & Jacobsen (2002), they concluded that the trading strategy based on this Halloween effect is not significantly outperforming the Buy-and-hold strategy.

Some other studies besides the already mentioned confirmed the existence of the Halloween effect on different stock markets, too. We should mention Haggard & Witte (2010), Witte *et al.* (2010), or Maberly & Pierce (2003).

Haggard & Witte (2010) used data from the Center of Research in Security Prices 1926 to 2008 for their analysis. They found evidence of the Halloween effect on the researched stock prices for sub-periods 1954-1980 and 1981-2008. They further researched the link between January and Halloween effects. The relationship in question is pretty straightforward, one might simply suggest that the unusually high returns from November through April are just high January returns in disguise. By this term is meant that the higher returns for the November through April are driven mainly or exclusively by high January returns. Haggard & Witte (2010) implied that the anomaly in question

[1] Jacobsen & Zhang (2014) reported on the article from 1935 and suggested that "Sell in May, go away" was already established adage at that time.

have sizeable magnitude over the two before-mentioned sub-periods even after adjustment for January effect was made.

Maberly & Pierce (2003) found evidence in the favour of this anomaly on Japanese stock market, but only prior to the internalisation of Japanese financial markets in mid-1980s. On the other side, they draw the attention towards huge opportunity cost of following trading strategy suggested by Bouman & Jacobsen (2002) on Japanese stock market in year 2003. Nikkei 225 index is stock index composed of 225 most significant stock of Japanese companies traded on the Tokio stock market. The index increased by 34.15 percent between May and October 2003 which implies large opportunity cost for investors following the trading strategy proposed by Bouman & Jacobsen (2002).

Maberly *et al.* (2004) analysed dataset for U.S. stock markets for the period 1982-2003. This study takes a closer look on the results presented by Bouman & Jacobsen (2002). Main focus of this study is the impact of outliers and January returns on the results on Halloween effect. After adjusting for the outliers, a conclusion was made that the Halloween effect disappears on the researched stock indexes.

Witte *et al.* (2010) questioned the results presented by Maberly *et al.* (2004) and stated: "*Maberly and Pierce deal with outliers in an unsatisfactory way*" and that better methods of confronting influential data produce results very similar to those first reported in Bouman and Jacobsen. Mainly, Witte *et al.* (2010) criticised the selection of outliers and suggested few additional observations to be also characterized as outliers. Furthermore, he performed three different robust regressions that are not as susceptible to outliers and claimed that the results match the findings of Bouman & Jacobsen (2002).

Lucey & Zhao (2008) looked on this phenomena on U.S. stock markets in the period from 1926 to 2002. Their results did not agree with already mentioned Bouman & Jacobsen (2002) in a sense that there was not enough evidence on the Halloween effect. They also researched the link between January and Halloween effects. They concluded that the evidence for Halloween indicator is *"weak, at best"* for their researched data.

The point of our interest is the same as in the case of January effect, it is the conflict with the claim on market efficiency. This case of seasonal anomaly is even more striking in comparison with January effect since there is available trading strategy, which is supposedly more profitable than simple "buy-and-hold" strategy, proposed by Bouman & Jacobsen (2002). This should imply that every rational investor would follow this or another strategy using the available information.

Possible explanations are presented for example in the Bouman & Jacobsen (2002). The most convincing explanations include already presented link between Halloween and January effects and vacation related explanation. The first possibility suggests that the Halloween effect is driven mainly by high January returns and it is only another manifestation of the January effect. The second explanation linking vacations and high returns on equity considers two plausible causes. Firstly, it implies that unanticipated negative change in number of investors or unanticipated positive change in risk-aversion should lead to decrease in the overall will to bear risk. Hence, this should lead in the end to the tendency of active investors to aim towards higher risk premium. The second implication of vacation influencing the returns on stock claims that the investors are more financially limited after summer vacations and then they have tendency towards higher liquidity premium on equity during winter.

Overall review of previous research

Overall, studies focusing on research on international level more often than not acknowledge the difference between returns on stock between November-April and May-October periods. Most notably, Jacobsen & Zhang (2014) or Bouman & Jacobsen (2002) confirmed the presence of Halloween effect on majority of 108 and 37 researched countries, respectively.

The results for U.S. market are somewhat mixed. Maberly *et al.* (2004) gave credit of the presence of Halloween effect to few outliers found in their data from 1970 to 1998, whereas Lucey & Zhao (2008) stated that the evidence of the anomaly is *"weak, at best"* and tried to explain it by January effect. On the other hand, Witte *et al.* (2010) and Haggard & Witte (2010) found evidence for the anomaly on U.S. stock data (for the period after 1954) with the use of similar data used by Maberly *et al.* (2004) and Lucey & Zhao (2008). Jacobsen & Visaltanachoti (2009) researched deeper into this problem and claimed that the results are dependent on the type of industry.

2.2.3 Turn-of-the-Month Effect

As with the above mentioned anomalies, this one is linked with disproportionately high returns on equity during certain time period. For this effect the concerned period is the last trading day of the month and first three trading days of the following month. The first study to detect this particular anomaly was Ariel (1987). He came up with the research after being inspired by evidence on other calendar effect such as January and Monday effects. Analogically to other effects, our interest lies in the conflict with Efficient Markets Hypothesis since there is evidence that this seasonal anomaly persists on stock markets long after its discovery.

The first analysis focused on this issue was conducted by Ariel (1987). Ariel (1987) used data on U.S. stock markets from period 1963-1981. This study featured comparison between returns during the first half of the month with the second half. For convenience Ariel (1987) defined the trading month from the last day of the month (inclusive) to the last day of the following month (exclusive). His results then suggested that the difference for returns between the first and second halves of the trading month was evident for the entire researched period.

Kunkel *et al.* (2003) is another study confirming this anomaly. This study analysed data from 19 countries all over the world (years 1988-2000). This paper dealt with the Turn-of-the-Month effect in terms of four days around the turn of the month beginning with last day of the particular month. Their results showed that the effect is present on 16 out of the 19 markets covered. They also claimed that 87 percent of average monthly returns are accumulated during the 4 day long period around the turn of the month.

Lakonishok & Smidt (1988) found strong evidence on this anomaly across 90 years of data for Dow Jones Industrial Average index. This study used data beginning in 1896. The anomaly was defined as the first three trading days of month and the last trading day of previous month. They concluded that the anomaly was indeed present in the researched Dow Jones Industrial Average index, but they also stated that they lack evidence for any relationship between this anomaly and other stock seasonals that would help to explain the Turn-of-the-Month effect.

On the other hand, there are studies, which produced inconclusive results, such as Jaffe & Westerfield (1989) or Cadsby & Ratner (1992). The first one looked deeper on the anomaly in Canada, United Kingdom, Australia and Japan. They found significant evidence only for Australia. But what is more interesting, strongly significant evidence on negative effect for Japan. Authors were unable to uncover the causes related to these results.

Cadsby & Ratner (1992) researched the issue of returns on stock around the turn of the month in Canada, United States of America, France, United Kingdom, West Germany, Switzerland, Japan, Hong Kong, Italy and Australia. In the end, they came with a conclusion that the evidence supporting the anomaly was not convincing.

Now, we turn our focus to possible explanations. Already mentioned Ariel (1987) went through several possibilities only to turn down every option except the link to small firms and January effect. He states that after adjustment for small firms in terms of January effect is made, the Turn-of-the-Month anomaly is no longer present in the original magnitude. It is important to note that this explanation is just partial since it involves only small firms and the Turn-of-the-Month effect can be detected on the market as a whole.

Another possibility was offered by Ogden (1990), his suggestion stated that the increase in returns for days around the turn of the month can be attributed to increase in demand. His study of data for U.S. stock markets supported this hypothesis. Ogden (1990) argued that this increase in demand is caused by standardization of payments with pay-off date being generally set on the end of the month.

Overall review of previous research

Some pattern in previous research is visible in the studies carried out on international specimen of data. Earlier studies from Jaffe & Westerfield (1989) and Agrawal & Tandon (1994) have not found convincing evidence on the presence of Turn-of-the-Month effect, whereas later studies such as Kunkel *et al.* (2003) and Giovanis (2009) found evidence convincing enough to acknowledge that the presence of this seasonal anomaly might be present.

2.2.4 Monday Effect

The Monday effect, also known as Weekend effect, is one of the calendar effects, same as January or Turn-of-the-Month effects. The evidence about returns on equity on Monday do not follow neither trading time hypothesis nor calendar time hypothesis. The first one claims that returns on Monday should not be significantly different from any other day of the week. The second claims that the returns on Mondays should be three times higher than returns for any other day of the week since Monday follows after two non-trading days (French

1980). This hypothesis stands on longer holding period and greater risk over the weekend.

The paper of French (1980) was among the first ones to draw the attention to this seasonal phenomenon. French used data on Standard and Poor's composite portfolio between years 1953 to 1977. The outcome of the analysis is that Mondays do have significant negative returns, different from the other days of the week. French also stated *"...it is difficult to imagine any reasonable model of equilibrium consistent both with market efficiency and negative expected returns to a portfolio as large as the Standard and Poor's composite"*, which shortly describes the problem connected with Weekend effect. This study also pursued the link with returns after holidays in order to discover if the anomaly is related with closed markets. The results disproved this kind of link and therefore it should be obvious that the anomaly is caused by some kind of "Weekend Effect".

Other studies including Wang *et al.* (1997) or Sun & Tong (2002) were able to confirm such seasonal effect, but only for the last two weeks of the month. The latter explained these results with selling pressure from individual investors which proved to be higher at the end of the month. Sun & Tong (2002) also suggested that negative returns on previous Friday influence the negative Monday returns.

The study by Wang *et al.* (1997) found evidence that returns on equity in the first three Mondays of the month are not significantly different from zero. They supported the idea that negative Monday returns are driven mainly by the drop in returns for the fourth and fifth (where present) Monday of the month. On the other hand, this paper proposed that after controlling for results on previous trading day, Weekend effect can be found at least for the fourth Monday of the month.

The relationship between returns on Mondays and returns on previous trading day was followed by Keef *et al.* (2009), too. They implied that the Monday effect is solely caused by the prior-day effect, which suggests that changes in stock prices are influenced by and follow the results of the previous trading day.

Draper & Paudyal (2002) used data for United Kingdom in their study. They concluded that after controlling for several different factors, such as trading activity, dividends or arrival of news, the Monday effect was no longer present.

The results in study by Mehdian & Perry (2001) are somewhat mixed and can be viewed as confusing. But the outcome is that they detected Monday effect for most of researched stock indices (mainly driven by negative returns in the last two weeks) prior 1987 and that Monday returns do follow the results of previous trading day. It is worth pointing out that they found reversal in the effect. For three of their five indexes they found evidence on positive returns on equity (but not significantly different from other days of the week) on Mondays. These indexes were large-cap U.S. indexes for the period 1987-1998. This implies that after the anomaly got more attention in the 1980s, the effect reverted itself for some parts of the markets. This process is also known as Murphy's law on market anomalies. This version of the well-known Murphy's law suggests, according to Dimson & Marsh (1999), that any predictability is impossible. That implies that when persistence of anomaly is expected, it will disappear or revert itself and whenever reversion is expected, the anomaly will persist. On the other hand, Mehdian & Perry (2001) were also able to detect evidence of negative and lower returns on Mondays in comparison with other days of the week for two U.S. small-cap indexes in the same period.

Overall review of previous research

Common characteristics of previous research carried out on the U.S. stock market is the agreement that the Monday effect, if found, is mainly driven by the returns of last two Mondays of the month. Mehdian & Perry (2001), Draper & Paudyal (2002) or Sun & Tong (2002) claim that for their researched data, the returns on equity in the last two Mondays of the month are especially low and therefore these two days of the month drag the results for the returns down.

As far as international and more up-to-date research goes, the trend is that often no significant results in favour of Monday effect are found, as Keef *et al.* (2009) or Giovanis (2009) reported.

Chapter 3

Methodology and Data

3.1 Methodology

Ordinary Least Squares

Ordinary Least Squares (OLS) method is used for the analysis. It is linear regression method where the sum of squares of the errors is being minimized. It allows us to analyse various relationships between two or more variables (one dependent and one or more independent variables).

This approach has substantial advantages, at least for the case of seasonal anomalies on stock markets. Firstly, the proposed relationship is straightforward and simple to interpret and evaluate after the use of specified model. Secondly, the use of binary (also known as dummy) variables corresponds well with the analysis of seasonal effects. These variables are equal to one for the specified period (or certain group of people, observations from some area, etc.) and zero otherwise. We categorize the monthly and daily classification of our observations through these binary variables and therefore we are able to distinguish between the returns for the given season and the other seasons.

But there are some disadvantages to this approach, too. Most of all, specific requirements need to be met in order for the estimates to be consistent and for the validity of related statistical inference. Consistency requires first three assumptions (in Section 3.1) to hold and it tells us that the estimates converge in probability towards the true parameter with increasing amount of data. The validity of statistical inference requires all of the assumptions to be met and it allows us to perform the concrete t-tests and other statistical tools used for our analysis.

Regression Models

Generally, in this thesis there are two types of models used. Though they are somewhat similar (for example in their implementation, use of related statistical tests or use of binary variables) it is useful to take a closer look on their interpretation and their use.

The first type can be specified with this equation:

$$Change_t = \alpha + \sum_{j=2}^{J} \beta_j D_j + e_t \tag{3.1}$$

where α represents the intercept. β_j denotes coefficient relevant for every individual dummy variable D_j, with J being the total amount of the appropriate seasons (5 trading days in the week or 12 months a year) and e_t is the error term (the index t marks time). Dummy variable related to the researched period (January or Monday) does not appear in the equation to avoid the perfect collinearity problem. Therefore the expected returns for such period are hidden under α and thus we test the statistical significance and investigate the sign of the intercept. For example when analysing the Monday effect, we would end up with 4 binary variables for Tuesday through Friday and an intercept, which is of our interest.

Due to suitability of the first model, its interpretation and definitions of the Halloween and Turn-of-the-month effects, the first model is used only for analysis of January and Monday effects. Similar or identical models were used for example in Gultekin & Gultekin (1983), Mehdian & Perry (2001) or Agrawal & Tandon (1994) studies.

The second type follows the equation:

$$Change_t = \gamma + \delta D + e_t \tag{3.2}$$

where γ represents the intercept, δ the estimated coefficient relating to our dummy variable D and e_t is the error term (the index t marks time). $Change_t$ marks the change in index values (daily or monthly, depending on researched seasonal effect) and the dummy variable D marks our desired period, which equals 1 for observations from the specified period and 0 elsewhere.

Coefficient δ is of our interest in these regressions since expected returns outside the desired period equal to γ and expected returns for the given period equal to $\gamma+\delta$. It is the difference δ that tells us whether returns for such period are higher or lower in comparison with the rest of the year/month/week. In researching Halloween effect for example, we would expect positive and statistically significant coefficient to confirm the claim that returns are higher in November through April than returns for the rest of the year.

Models of this character were used by Bouman & Jacobsen (2002), Kunkel *et al.* (2003) or Cadsby & Ratner (1992) just to mention few. For its straightforward interpretation and simplicity, this model is used for the analysis of all four seasonal effects.

The difference in the interpretation of these two different types of models is following: the first model tests if the expected returns are positive or negative for the desired period and compares them to other months/weekdays. The second model tests the difference between the desired period and the rest of the season (year, week or month).

Assumptions and related statistical tests

The assumptions needed for OLS (sometimes called "Asymptotic Gauss-Markov Assumptions") are:[1]

1. **Linearity in parameters, stationarity and weak dependence**

   The models specified in Equations 3.1 and 3.2 are linear in parameters. The weak dependence assumption should hold from the character of stock markets. The returns on stock markets should not be dependent (or should be weakly dependent, at most) on the previous results since that would present stock market agents opportunity for profit. The stationarity assumptions is tested by the Dickey-Fuller test.

2. **No perfect collinearity**

   We avoid this problem by omitting dummy variables for some specific time periods (January and Monday) in certain models.

3. **Zero conditional mean**

[1] For more detailed information on Ordinary Least Squares method, the assumptions and related statistical tests and procedures see Wooldridge (2012).

This assumption should hold, because it is reasonable to expect that the error in given time period is uncorrelated with our seasonal binary variables, i.e. errors are not dependent on the current season.

4. **Homoskedasticity**

   We could expect some problems with the homoskedasticity since the variance of the errors could be changing with time and seasons. With the behaviour of stock markets in mind, some doubts are in place and hence we test the homoskedasticity assumption with Breusch-Pagan test. In the possible presence of heteroskedasticity, robust standard errors were used to deal with the problem.

5. **No serial correlation**

   We should not discard the possibility of the errors being serially correlated. Breusch-Godfrey and Durbin's alternative (in the presence of heteroskedasticity) tests for a possible lag of one unit (day or month) are applied in order to verify the validity of this assumption. In the presence of serial correlation, Prais-Winsten procedure is used to correct for it. In case of both, heteroskedasticity and serial correlation, so-called Newey-West standard errors are used.

Breush-Pagan test is a statistical test used for detection of heteroskedasticity. It is performed by obtaining residuals from the specified regression and then regressing these squared residuals onto all explanatory variables from the original regression. If these are jointly significant, we cannot discard the possibility of present heteroskedasticity.

If the homoskedasticity assumption is violated, one of the possible solutions are heteroskedasticity-robust standard errors. The appeal of this method is that the coefficients stay the same with the exception of corresponding standard errors. These errors take into account heteroskedasticity of unknown form, making it simple to use. The downside of this method is widening (in most cases) of the underlying confidence intervals.

Breusch-Godfrey test is one of possible tests when dealing with serial correlation. It tests for serial correlation not specified in the model (i.e. possible misspecification of the model). The test searches for relationship between residuals at time t with its lagged counterparts up to the specified lag by regressing the obtained residuals from the original regression onto all explanatory variables and lagged residuals up to p-th lag. Then F statistic or LM statistic can be used for the test of joint significance of the lagged residuals. We decided to set the possible lag at one unit (day or month). Since Breusch-Godfrey test is not suitable in the presence of heteroskedasticity, we use Durbin's alternative test in such situations.

Durbin's alternative test is used to test for serial correlation by testing the relationship between lagged residuals and the contemporaneous residuals from the original regression. For the lag of order one it is performed as follows: we obtain residuals from our specified model and regress the residual at time t onto all regressors from the original model and the lagged residual at time *t-1*. Then t-statistic is used to test the relationship between the residual at time t and time *t-1*. This test, unlike the Breusch-Godfrey, can be made robust to heteroskedasticity by using robust t-statistic in the last step.

Prais-Winsten procedure is a special type of Feasible Generalized Least Squares method used to deal with the serial correlation problem. This procedure uses quasi-differenced data in order to deal with the serial correlation. Asymptotically, this approach is more efficient than OLS if serial correlation is present.

Newey-West standard errors are similar in their usage to heteroskedasticity errors. The original coefficients of the regression stay the same and the standard errors change in a way to accommodate for possible heteroskedasticity and serial correlation. Their appeal is also their simple implementation into our OLS models.

3.2 Data

Data used for the analysis consists of 32 selected European stock indices. For every respective country and its stock market, corresponding stock index was chosen. Were there more possible indexes, so-called large cap indexes were chosen. Firstly, in order to be consistent (both across our selected indexes and with previous research on seasonal effects) and secondly because these are simply most used and acknowledged indexes. The indexes are mostly composed of the largest, most successful and/or most liquid stock on the market. Often, the stocks included in these indexes are described as the "blue chip". This notion is used for companies with high market capitalization that are stable, established, have good reputation and are often viewed as a sound and safe investment. Despite the fact that the indexes are often constructed in a way to represent the corresponding market, we should be aware of the composition of the indexes. The composition tells us that indexes often represent only part of the market and not the market as a whole. And although we refer to these indexes as representatives for each stock exchange and country, we should bear in mind that they might not always show the true reality of the entire market. But after considering these issues, we still believe that this is the best approach towards this kind of analysis featuring such a high amount of national markets.

Indexes used in this thesis are of national character, which means that only stock traded on domestic markets are included. There are also regional or global stock indices, like EURO STOXX 50 (European index of 50 leading stock), OMX NORDIC 40 (regional index of 40 most traded stock from Copenhagen, Helsinki, Stockholm and Reykjavík stock exchanges) or S&P Global 100 (global index of 100 international large-cap companies).

Opposed to large-cap indexes, there are small-cap indexes, which constitute of the smaller or smallest companies listed on the specific stock exchange, e.g. FTSE SmallCap Index.

An all-share-index is composed of all the listings on the given stock exchange after meeting some admission criteria. Swiss All Share Index is fine example for SIX Swiss Exchange.

When computing the index, different types of weights might be used with market capitalisation, equal, free-float and price weighting being the most common. Market capitalisation weighting takes the size of the company into account, whereas in the equal weighting all firms have the same influence on the results of the index. Free-float weighting uses the number of shares in the hands of public investors or outsiders as the benchmark and price weights take the price of the stock as the only deciding factor.

The term return in this thesis is simply defined as equivalent to a change in value of the indices. For the analysis of Halloween and January effects "open to close" change was used, which is simply percentual difference between the opening value on the first trading day and the closing value on the last trading day of the month. For our research on Monday and Turn-of-the-Month effects "close to close" changes are used. The definition of Monday effect from Section 2.2.4 is a change from Friday close to Monday close and hence the "close to close" is chosen to also capture the changes happening during the weekend. Occasional lack of opening daily values for the indexes played also key role in this choice. “Open to close” changes are used for Halloween and January effects to avoid the changes in index values not happening in our specified period.

List of the indexes and their short characteristics are in Appendix A. Although the used datasets start differently, most of them consists of circa last 20 years with ending on the last trading day of February 2016 (except for Greek index FTASE, where we used data up to last December 2015).[2] The shortest obtained dataset is for Polish WIG 30, which consists only of 39 months. On the other hand, British FTSE 100 is the longest dataset with 386 month, beginning in January 1984.

Descriptive statistics of used data

	Longest dataset	Shortest dataset	Average dataset
Monthly data	386 months (FTSE 100)	39 months (WIG 30)	219.2 months
Daily data	8374 days (FTSE 100)	787 days (WIG 30)	4577 days

	Largest increase (in %)	Largest decrease (in %)
Monthly data	50.53 (FTASE)	41.10 (CROBEX)
Daily data	76.93 (PFTS)	48.40 (PFTS)

Table 3.1: Descriptive statistics of used data

The largest monthly percentage change recorded in our data was March 1998 for Greek FTASE index. Drachma, former Greek currency, entered the European Exchange Rate Mechanism, which had positive influence on Greek financial markets and resulted into 50% increase in the stock index value. On the other side we have the largest decrease from our dataset, which was recorded for Croatian CROBEX index. In 1998 Croatian banks experienced crisis, where some of them were found vulnerable towards macroeconomic development. This resulted into 41% decrease in the value of CROBEX.

The biggest percentage swings for daily data are for Ukrainian PFTS index. Although the changes are large in relative numbers, they are small in absolute values (around 16 and 18 points increase and decrease, respectively). The market was overall volatile in the past as far as the daily changes go, but since these biggest changes happened only few days apart in December 1998, they

[2] Although some of the datasets may begin on the same day or month, the number of daily observations may differ due to diverse national holidays or some extraordinary periods when the trading was suspended, e.g. Orange Revolution in Ukraine, several days in September 2008 in Russia, etc.

partially negated each other and in terms of monthly open to close changes, the market was reasonably stable with only -1.24% change in PFTS value.

On the European stock markets, there are groups operating several stock markets. Nasdaq OMX Group operates NASDAQ Stock Exchange and seven European stock exchanges. After failed bid on London Stock Exchange, Nasdaq acquired OMX (which at that time operated the Nordic and Baltic stock exchanges) after deal was made with Borse Dubai, which was also interested in acquisition of OMX. After long and complicated transaction, Nasdaq completed the acquisition of the OMX and its stock exchanges.

Euronext is European stock exchange with five branches in Western Europe (Amsterdam, Brussels, Lisbon, London and Paris). After merger with NYSE and its acquisition by Intercontinental Exchange, Euronext separated itself, to gain independence again, from Intercontinental Exchange. Now it is standalone company with a group of international investors throughout the financial sector holding significant minority.

Chapter 4

Results

4.1 January Effect

For analysis of the January effect, we use two different models, which are generally specified in Section 3.1. The first model (Model 1) follows the equation:

$$\begin{aligned} Change_t = \alpha &+ \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + \beta_6 D_6 + \beta_7 D_7 \\ &+ \beta_8 D_8 + \beta_9 D_9 + \beta_{10} D_{10} + \beta_{11} D_{11} + \beta_{12} D_{12} + e_t \end{aligned} \tag{4.1}$$

where $Change_t$ denotes open to close change (i.e. opening value on the first trading day of the month and the closing value on the last trading day of the month) in index values (same as in the Halloween case), D_m represents dummy variables for respective months, beginning with February, β_m is the corresponding estimate and e_t is the error term. The binary variable for January is omitted on purpose to avoid the collinearity problem. The interpretation resulting from this model is following, $\beta_m + \alpha$ is the expected change in the m-th month of the year and α is the return on stock in January. From this definition, we would expect the intercept α to be positive. To discover the unusually high returns for January, statistical significance and magnitude of the estimate are of our interest. A brief look on results of the other coefficients will help us in the analysis as well.

The other model (Model 2) is one of the models specified in Equation 3.2. It follows the equation:

$$Change_t = \gamma + \delta Jan + e_t \tag{4.2}$$

where $Change_t$ denotes, again, the open to close change in index values, Jan represents the dummy variable, which equals one for the changes during January and e_t is the error term. To be able to claim that we have found evidence of presence of the January effect on European stock markets, the sign, statistical significance and magnitude of the estimated coefficient are of interest. Interpretation of this model is simple, the expected returns for January are equal to $\gamma + \delta$. Hence, expected sign of the coefficient δ is positive.

Tables 4.1 and 4.2 present the acquired results from 32 analysed European stock indexes.[1]

Overall the results do not demonstrate convincing arguments on the presence of the January effect on the researched markets. In this case, Model 1, which presents the performance of stocks in January, suggests that the returns on stock may be positive in this month. This claim is supported with 78% positive estimates for the correspondent coefficient with 3 significant at 10% level (OMC 20 for Copenhagen) and 2 of those being statistically significant even at 5% level (OMXT for Tallinn and OMXV for Vilnius). However, the statistical significance is not that convincing and the comparison with other months does not suggest that returns in January are significantly higher than in the other months either. The amount of negative coefficients for May, June, August and September may suggest lower returns for these months, but the lack of substantial statistical significance dismisses this proposal, too.

The result for OMXT begs for closer look because of unusual positive magnitude of the coefficient. Expected return on stock is 5.6% for January. That is one of the highest suggested returns in this model. From brief look on the development of historical prices of OMXT, we can infer that the results may be affected because of outliers. Outlier is by definition an extreme observation, in the case of stock markets extreme swings, either increase or decline, in the values of indexes. The used OLS regression is sensible towards these kind of observations. The most interesting observation for January is in 2010, the increase in OMXT was nearly 45% during single month. This is by far the

[1] Results statistically significant at 5% level are stated both in the 5% and 10% category. Results statistically significant at 1% level are stated in categories for 1%, 5% and 10%. More detailed results of both models are in Appendix A.

Model 1	January		February		March		April		May	
estimates α and β_j	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.
overall	7	25	15	17	18	14	12	20	27	5
significant at 10%	0	3	2	2	0	0	1	3	3	0
significant at 5%	0	2	2	0	0	0	0	0	3	0
significant at 1%	0	0	0	0	0	0	0	0	0	0

	June		July		August		September		October	
estimates α and β_j	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.
overall	28	4	18	14	26	6	29	3	17	15
significant at 10%	5	0	0	0	2	1	6	0	3	1
significant at 5%	3	0	0	0	0	1	1	0	2	0
significant at 1%	0	0	0	0	0	0	0	0	0	0

	November		December	
estimates α and β_j	neg.	pos.	neg.	pos.
overall	18	14	11	21
significant at 10%	1	1	0	2
significant at 5%	0	0	0	0
significant at 1%	0	0	0	0

Table 4.1: Results of the 'January' regressions for Model 1

biggest change (the closest to this are 35% changes) in the dataset for OMXT. In January 2010 the market reacted to the rumours about Estonia and its entry into the eurozone. Soon, the market was detected as one of the best performing markets in the world, which attracted more and more investors and the stock price increases escalated. Therefore the result for OMXT should be taken with consideration of this observation.

Outcome for the Model 2 is even more inconclusive. Only 3 positive estimates are statistically significant, all of them on 10% level. OMXT and OMXV are present in this group with the third one being SBI TOP from Ljubljana. For the same reasons as in the preceding paragraph, results for OMXT should be approached with slight caution.

Although circa 60% of the estimates are positive, we found one that is negative and statistically significant (OBX index for stock market in OSLO). January's 20% downward swing for OBX in 2008 is worth of noting. It is the third biggest monthly change for this index, right behind September and

	Model 2	
estimates of δ	negative	positive
overall	13	19
significant at 10%	1	3
significant at 5%	0	0
significant at 1%	0	0

Table 4.2: Results of the 'January' regressions for Model 2

October in the same year. The cause for September and October changes is obvious, the Global Financial Crisis. The cause of January's swing is more subtle. New rules for stock market agents were set up with effect from the start of 2008. These changes were introduced to achieve more efficient markets and higher harmonisation with markets within EU. On the other hand, this is not even the biggest swing in the dataset, thus the results should be trustworthy.

Global Financial Crisis of 2008

This crisis is referred to as the second worst financial crisis in history, right after the crisis in 1930s. The main cause of this crisis was the burst of the bubble on the market with mortgages in United States. This resulted in major liquidity problems for banks worldwide because of close relationships between banks on international level. The crisis resulted in several bailout packages for banks, the fall of Lehman Brothers and hence in uncertainty on the stock markets, including Europe. The impact on the outcome of our research on seasonal effects is clear, because the most dramatic drops in stock prices incurred mainly in September and October, i.e. non-January period with suggested lower returns on stock. To be concrete, we can mention 13%, 28% and 25% decreases of value for FTSE 100 (September 2008), PX (October 2008) and OBX (September 2008), respectively.

All in all, the evidence for January is questionable, at best. Although positive returns on January may not be scarce, our results cannot reliably confirm that January returns are higher than returns for any other month. Any generalisation is also hard, but from the Model 1 it might seem that countries in Northern Europe (if we count in Baltic states) might be decent representatives of January effect, but negative and statistically significant estimate for Norway dismisses that. Hence, the claim holds reliably only for Estonia and Lithuania.

4.2 Halloween Effect

For the analysis we use the regression model specified in Equation 3.2. For the analysis of Halloween effect, the desired model includes only one explanatory dummy variable and the intercept and follows the equation:

$$Change_t = \gamma + \delta Hal + e_t \tag{4.3}$$

where $Change_t$ means open to close monthly percentage change in the analysed stock index. The dummy variable Hal equals zero for period May through October (inclusive) and one for the rest of the year, that is November through April, since this is the period we want to analyse. According to this model, we would expect the coefficient δ to be positive and statistically significant, if the saying "Sell in May, go away" is to be true for our data. Our focus is therefore on the sign, statistical significance and magnitude of the δ coefficient. Error term is represented by e_t.

Table 4.3 sums up the results obtained from the 32 analysed European stock indexes.[2]

estimates δ	negative	positive
overall	3	29
significant at 10%	0	13
significant at 5%	0	11
significant at 1%	0	6

Table 4.3: Results of the 'Halloween' regressions

As we can see, 29 out of the 32 regressions yielded positive coefficients. All of the negative coefficients were statistically insignificant on top of that.

[2] Results statistically significant at 5% level are stated both in the 5% and 10% category. Results statistically significant at 1% level are stated in categories for 1%, 5% and 10%. More detailed results of the model is in Appendix A.

But more importantly, circa 90% of the coefficients were estimated positive. Moreover, around 40% of the positive estimates are statistically significant at least at the 10% level. Such results are pretty straightforward and the first look suggests that the Halloween effect is indeed still present on the chosen European markets.

To be more specific, the negative estimates were for OMX RIGA for Latvia, WIG 30 index from Warsaw Stock Exchange and SOFIX, the official index for Bulgarian Stock Exchange. Such a result for WIG 30 may be partially due to small dataset used for the analysis. The dataset covers only 3 whole years of trading and it is the smallest dataset used for the analysis. Further, the estimated coefficient for Bulgarian Stock Exchange index was particularly small in magnitude (it suggested that returns for the non-Halloween period were higher by only six thousandths of percentage point than the returns during the November through April period). And as far as the OMX RIGA goes, there are two outstanding upward swings in the non-Halloween period, that might have affected the outcome. The first one is 34% rise in the index value for July 2001. First factor behind this rise is the start of “Financial and Capital Market Commission”, which is public Latvian institution established for the purpose of supervision over private financial sector. This step brought trust towards the Latvian financial sectors and hence influenced returns on the stock exchange. Second factor was overall good state of Latvian economy throughout the whole year of 2001. The second outstanding observation is September of 2015 with 30% increase. This was caused by huge change in the value of shares of Ventspils Nafta AS, Latvian company dealing with oil transportation. At the end of September, the shares reached multiple times its value from the beginning of the month due to the increase of stake of Vitol SA, another oil trading company, in Ventspils up to 93%. Those two substantial increases on the market might have some weight in the negative result of the coefficient.

Further look into the results does support the claim of higher returns on stock during the November through April period, because 12 of the 14 significant positive coefficients are still statistically significant even at 5% level and almost one fifth out of all the observed stock indices produce outcome significant at 1% level. These results include OMXS 30 index for Stockholm’s market, ATX for Vienna, CAC 40 for Paris, FTSE 100 for London, ISEQ Overall for Dublin and PFTS index for Kiev. The estimate produced for the PFTS index, which is the biggest from all the estimates (the output suggests that returns on stock during the November-April period are bigger than during the rest of the year by 5 percentage points), asks for a closer scrutiny. Since the changes of PFTS index include swings bigger than 20% on various occasions, these observations may have significant effect on the results.

If we take a closer look on the data for other the most significant indices, some pattern can be observed, too. Most of them could be influenced by some events that influenced stock markets worldwide. There were several considerable downturns on the markets in the last 20 years during the "non-Halloween" period. These downturns are mostly connected to major events influencing financial markets around the world, the most important are August and September in 1998 (Russian financial crisis), September in 2001 (attacks on World Trading Center), September in 2002 (Bursting of so-called "Internet bubble") and several months of 2008 (Global Financial Crisis). Since all of these events coincide in the May through October period, it is possible that the results are influenced by these events and hence the results should be taken into account with a bit of caution.

Russian financial crisis of 1998

In 1998 Russia battled with chronic fiscal deficit, decline in productivity and unsustainable fixed exchange rate of rubble against American dollar. With declining price of oil, wide strike of coal miners in May 1998 and Asian financial crisis in the preceding year in the mix, the struggle of Russia magnified. The uncertainty and absence of unified anti-crisis policy after change of the entire cabinet in March 1998 led foreign investors to vacation of Russian markets. Such events together with resulting default on domestic debt led, among other things, towards major downturn on stock market that spilled on several other European financial markets. This resulted into 35% drop in value of BET 10 (Romania) or 34% decrease in BUX (Hungary) index in August 1998.

Attacks on 11th September

On 11th September terrorist group Al-Qaeda attacked four different U.S. targets using suicide bombers and hijacked planes. These attacks left thousands of casualties with the targets being World Trade Center (also known as "Twin Towers"), Pentagon and the last plane crash on a field near Shanksville, Pennsylvania after the passengers were able to neutralize the hijackers. These attacks resulted even in closing (or more precisely not opening) Wall Street until

17th September. Naturally, the aftermath of these attacks included sharp declines on stock markets not only in U.S., but worldwide including indexes in our analysis. For example, German DAX decreased by 17% during the September of 2001.

Stock market decline in 2002

The decline on global stock markets in September/October 2002 was one of the effects of "Dot-com bubble burst" during years 1999-2001. Growth in commercial use of internet together with rising stock market promised great returns on stock issued by companies which name ended with *.com*. Such companies, also called *Dot-coms* were very popular on stock markets. But the growing indebtedness of these companies resulted in burst of the bubble. This burst may have some influence on the results of our analysis through our chosen stock indices. Specifically, FTSE 100 experienced third biggest downward swing (10%) from our dataset and CAC 40 decreased by almost 17% experiencing its biggest drop in our dataset.

To sum up, our results suggest the presence of the Halloween effect on most of the chosen European markets. The main arguments are the positive sign of the coefficients for more than 90% of the indexes and decent statistical significance. It is apparent that countries from Western Europe have clear majority in the group of the most significant positive estimates. Hence, it can be inferred with slight caution that markets in Western Europe tend to exhibit this seasonal pattern more significantly than other European markets. On the other hand, the results need some caution behind the interpretation, since several global downturns can be spotted in the chosen dataset in the period May through October.

Halloween Effect as January Effect in Disguise

As suggested by Bouman & Jacobsen (2002), Halloween effect might be only another manifestation of the January effect. Although our analysis in Section 4.1 does not suggest that there is enough compelling evidence to safely confirm the presence of January effect on the researched markets, we continue with the analysis anyway. We follow with the model used previously, only with slight adjustment. Similar approach was used by Witte *et al.* (2010) or Lucey & Zhao (2008).

The used model follows the equation:

$$Change_t = \alpha + \beta_1 Hal^{adj} + \beta_2 Jan + e_t \tag{4.4}$$

where e_t denotes the error term, $Change_t$ same as previously the open to close monthly change in index values, α is the average yield on stock outside the "Halloween" period, Hal^{adj} is binary variable that equals one for November through April excluding January and Jan marks the binary variable for January. Thus we are interested in the coefficient β_1 and its sign, statistical significance and magnitude.

Should the Halloween effect be independent on the January effect, we would expect the coefficient β_1 to be positive and statistically significant. The table 4.4 summarizes the results of the 32 regressions.[3]

estimates β_1	negative	positive
overall	7	25
significant at 10%	0	15
significant at 5%	0	12
significant at 1%	0	7

Table 4.4: Results of the adjusted 'Halloween' regressions

The overall proportion of positive and negative estimates tells us that after adjusting for January, the Halloween effect is somewhat milder. But still, almost 80% of the coefficients remained positive, a convincing argument in favour of the Halloween effect after all. On the other hand, the statistical significance suggests stronger Halloween effect than in the original model (unadjusted for January), which might come as a bit of surprise. However, it is German DAX index, that became significant at 1% level after being significant at 5% level in the first model (just merely not significant at 1% level with p-value of 0.015). The other indexes significant at 1% level stayed the same with OMXS 30,

[3]Results statistically significant at 5% level are stated both in the 5% and 10% category. Results statistically significant at 1% level are stated in categories for 1%, 5% and 10%. More detailed results of the model is in Appendix A.

PFTS, CAC 40, FTSE 100, ISEQ and ATX. The rest of the sample mostly produced results similar to the previous regression.

The results of individual months from Model 1 (Table 4.1) of January effect gives us valuable insight for this issue. Although most of the coefficients provide somewhat "balanced" results in terms of their sign, for May, June, August and September the negative estimates have clear advantage. Despite the lack of substantial statistical significance, this suggests that the Halloween effect is not driven mainly by higher January, but rather by worse performance of the stock during several months from the "non-Halloween" period.

All in all, the results do not present enough evidence to discard the Halloween affect as the consequence of the January effect. This outcome could have been, however, awaited since the evidence on January effect is not particularly strong in out dataset.

4.3 Turn-of-the-Month Effect

This effect is analysed using the following model, which is more generally specified in Section 3.1. This regression model is similar to the one used for the analysis of Halloween effect. It includes one dummy variable and the intercept and follows the equation:

$$Change_t = \gamma + \delta Tom + e_t \tag{4.5}$$

where $Change_t$ represents close to close daily changes in researched stock index values, Tom representing the "Turn-of-the-Month" binary variable, which equals one for observations from the desired period and zero elsewhere and e_t signifies the error term. The first three trading days of the specific month and the last trading day of previous month are defined as our "Turn of the month" (which follows for example Lakonishok & Smidt (1988)). The interpretation together with our expectations are straightforward, the δ coefficient represents the difference between returns on trading days around the turn of the month and the returns for the rest of the month. Expected returns on equity for trading days during the turn of the month are $\gamma + \delta$, whereas returns on stock for the days not around the turn of the month is γ. Therefore, positive and statistically significant estimates of δ would be in place for confirmation of the seasonal effect in our data.

The results of the regression are summarized in the following Table 4.5.[4]

estimates δ	negative	positive
overall	1	31
significant at 10%	0	22
significant at 5%	0	20
significant at 1%	0	11

Table 4.5: Results of the 'Turn-of-the-Month' regressions

Vast majority of the regressions, 31 to be exact, yielded positive coefficients. Only one of the estimates was negative. This presents strong argument in favour of presence of the seasonal effect on European markets. But what is even more striking is the statistical significance, which the results present. More than one third of the estimates are statistically significant even at 1% level and around two thirds of the estimates are significant at 10% level. The amount of positive coefficients and more importantly the statistical significance suggest the presence of the "Turn-of-the-month effect" on the European stock markets.

The only negative coefficient suggesting smaller returns on stock during turn of the month than during the rest of the month belongs to OMX Riga, Latvian all-share index from Riga Stock Exchange. Although there are no substantial swings in the daily changes, which would result in more cautious interpretation of the results due to the outliers, we should still evaluate this outcome with some distance because of the lack of almost any statistical significance (the p-value is 0.451).

On the other end of the spectrum, there are the indices for which the regressions resulted in positive estimates statistically significant at 1% level. These indices are: ATX (Austria), BEL 20 (Belgium), BET 10 (Romania), BUX (Hungary), FTSE 100 (United Kingdom), ISEQ (Ireland), OBX (Norway), FTASE (Greece), OMXC 20 (Denmark), PSI 20 (Portugal) and SMI (Switzerland). On the first look, there is no visible geographical pattern. The interesting part is, that every region of Europe has multiple members in this group. Western Europe is represented by Ireland, United Kingdom and Belgium, whereas Eastern

[4]Results statistically significant at 5% level are stated both in the 5% and 10% category. Results statistically significant at 1% level are stated in categories for 1%, 5% and 10%. More detailed results of the model is in the Appendix A.

Europe has Romania and Hungary in this sample. Norway and Denmark are the representatives from Northern Europe, with Portugal and Greece from the South. Central Europe is in the mix also with Austria and Switzerland.

If we look at the data of these indices in more detail, no extreme observations, which could substantially influence the outcome in the favour of "Turn-of-the-Month" effect, are present. However it is still appealing to look at some of the bigger swings in the index values. The first and most influential event is the Global Financial Crisis of 2008. The crisis resulted in daily drops in the index values up to 13% for ISEQ and it is described in more detail in Section 4.1. The other influencing event is the decision of Switzerland's central bank to abandon the cap of franc against euro.

Switzerland's abandoning of the cap of franc against euro

The decrease of the value in SMI index on 15th January 2015 was result of Swiss central bank decision to loosen its exchange rate of franc against euro. This sudden and unexpected move spilled the uncertainty, panic and decrease in the central banks' credibility over to the stock market, that manifested itself in the 8.7% drop of SMI index.

In September 2011 the Swiss National Bank introduced a ceiling of 1.20 francs per euro to control for further appreciation of the Swiss currency. The central bank made this step to counter the overvaluation of franc and suggested that the value of the currency is a threat to the economy. This cap of franc was preserved until the 15th January 2015 when the Swiss National Bank decided to abandon this exchange rate policy. The central bank made such decision since the quantitative easing of European Central Bank, which would decrease the value of euro, was anticipated in the upcoming months and thus the overvaluation of the franc would no longer be a problem.

To sum up, the presented results of the regressions show substantial evidence for the presence of the "Turn-of-the-Month" phenomena on the European markets. The support of this claim can be seen in the amount of positive estimates and more importantly their strong statistical significance. Although no geographical pattern is visible in the outcomes, it is safe to say that the presence of this seasonal anomaly can be spotted throughout the whole Europe.

4.4 Monday Effect

Similarly to the January effect, two models are used. One with intercept and dummy variables for each day of the week, excluding Monday and the second one with the intercept and only one dummy variable for Monday. Hence, the first model (Model 1) follows the equation:

$$Change_t = \alpha + \beta_2 D_2 + \beta_3 D_3 + \beta_4 D_4 + \beta_5 D_5 + e_t \tag{4.6}$$

with interpretation being quite similar to the first model of January effect. $Change_t$ is the close to close daily change of index values. The binary variables, D_d, represent the dummies for Tuesday through Friday with omitting Monday to avoid the collinearity problem in the regression model. The error term is represented by e_t. Thus the expected returns for Tuesday through Friday are $\alpha + \beta_d$, expected returns for Monday are defined as α. Therefore, we would assume results for α to be negative to represent negative returns on Mondays, as suggested in Section 2.2.4. Look on the coefficients relating to Tuesday through Friday will help with the comparison of returns between Monday and the other days of the week.

The Model 2 with the following equation might be familiar to the reader. As with the other seasonal effects, this model includes only intercept and the corresponding dummy variable.

$$Change_t = \gamma + \delta MON + e_t \tag{4.7}$$

Same as in the preceding equation, the $Change_t$ denotes the daily changes of the chosen index values. The coefficient δ represents the difference between stock returns on Mondays and the rest of the week and e_t is the error term. Since we would like the returns for Mondays to be not only negative, but also lower than the returns for each day from the rest of the week, negative and possibly statistically significant coefficient would be in place.

The Tables 4.6 and 4.7 present the results of both models for the 32 chosen indexes.[5]

The presented outcome can be interpreted that the evidence for Monday

[5]Results statistically significant at 5% level are stated both in the 5% and 10% category. Results statistically significant at 1% level are stated in categories for 1%, 5% and 10%. More detailed results of the model is in the Appendix A.

	Monday		Tuesday		Wednesday		Thursday		Friday	
estimates α and β_j	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.	neg.	pos.
overall	23	9	10	22	8	24	6	26	5	27
significant at 10%	5	3	2	5	1	8	1	9	0	14
significant at 5%	3	2	1	2	0	5	1	7	0	10
significant at 1%	2	1	0	0	0	1	0	2	0	6

Table 4.6: Results of the 'Monday' regressions for Model 1

	Model 2	
estimates δ	negative	positive
overall	27	5
significant at 10%	12	1
significant at 5%	7	1
significant at 1%	4	0

Table 4.7: Results of the 'Monday' regressions for Model 2

returns being lower than returns for the other days is present, whereas the evidence on Monday returns being negative are somewhat mild. The difference is of course in the amount of negative estimates, but also in the statistical significance. In the first model, the estimates are negative only in circa 65% in comparison with almost 85% of the coefficients from the second model. On the other hand, we should not discard the results of the first model right away, after all, the negative coefficients exceed the amount of positive coefficients and the statistical significance is in the favour of negative signs as well. The comparison with other days of the week suggests that the returns are lower on Monday due to the amount of positive coefficients for other days of the week and at least some statistical significance. Interesting is the statistical significance of coefficient for Friday, which is not negligible. This would suggest that returns on stock for Fridays are significantly higher than returns for Mondays. But still, the results have to be taken into account as somewhat weak in comparison with the second model. Model 2 presents stronger evidence on the part of the seasonal effect that suggests lower returns on Mondays than for the rest of the week.

Some geographical pattern is visible if we take a closer look on the results of both models. For the first model, the positive and significant estimates for Mondays are for BUX, index for Budapest with 1% statistical significance, MICEX, index for Moscow with 5% statistical significance and OMXS 30 for Stockholm with 10% significance. On the other end of the spectrum, the most significant negative estimates (at 5% level) are for CROBEX (Croatia), FTASE (Greece) and FTSE/CYSE (Cyprus). Some of these results repeat themselves in the second model, the outcome for BUX is for example the only positive and statistically significant (at 5% level) estimate. Similarly, CROBEX, FTASE and FTSE/CYSE appear among the most significant and negative coefficients from the second model along with OMX RIGA (all of them being significant at 1% threshold). The suggested geographical pattern is clear, the Monday effect is best observed on data from Southeastern Europe. However, a short survey on the most substantial daily changes that might possibly influence the results of our regressions is also in place.

The most outstanding change in the value of BUX is 16.5% drop on 28th of October on 1997. This so-called "mini-crash" was a result of Asian financial crisis that influenced financial markets around the world and caused considerable drops in stock prices. The change in value of Russian MICEX 10 index on 19th of September 2008 might come as a big surprise since the index increased by an incredible 36.7%. To be more precise, it was change from closing value on the 17th of September until the closing value on 19th September because the trading was suspended for 18th due to high decreases on the Russian stock market (e.g. 21% drop on 16th of September). The reason for the sudden change on the market was the announcement of the Russian government to help the market with almost 14 billions of dollars including significant help for three of the biggest banks on the market. Despite the big percentage increase on 19th September, the MICEX 10 index only regained some ground and returned to the rates from 15th of September. However, the 19th of September was Friday and therefore as an outlier it could have influenced our second model (the one with only one dummy variable for Monday) in the favour of Monday effect, but the results for MICEX 10 were not statistically significant and hence should not pose any substantial problem in our results. Interesting is also the 29th August 2011 for the FTSE/CYSE index. The index increased surprisingly in a period of mostly decreasing stock prices, similarly to the Russian MICEX 10, it was a reaction of the markets on actions from Cyprian government. The government passed through the House of Representatives first package related to austerity measures concerning fiscal consolidation. But as far as our analysis goes, the

18% upward swing happened on Monday and hence it could have influenced our estimate only upwards. Since we are analysing returns on Monday, we should also take a closer look on "Black Monday", which marks the events on stock markets of October 1987.

Asian Financial Crisis and the 1997 Mini-crash

The problems started in highly indebted Thailand when the government decided to abandon the peg of its currency (baht) to the U.S. dollar. The Thai baht declined rapidly in its value afterwards, only causing more issues for the economy. The problems of high indebtedness and rapid devaluation of currencies spread throughout the Southeast of Asia and the financial markets were also hit by the events. Subsequently, the crisis hit Asia as a whole with European markets being affected also because of the existing connections. The crisis has partly contributed to the Russian financial crisis of 1998 described in Section 4.2. However, the influence on our results is not of any substantial interest since the 28th of October 1997 was Tuesday. This fact suggests that the surprising drop in value should not influence the results in the favour of the Monday effect. If it had any substantial impact, it would be in the favour of lower estimates for Tuesday dummy for Model 1 and the intercept for Model 2.

Black Monday of 1987

The "Black Monday" is a term referring to 19th October 1987 followed by "Black Tuesday" on 20th October. Several possible explanations like overvaluation of stock, illiquid markets and program trading were attributed to the worldwide stock market crash. The most favourite and appealing cause is the program trading, a type of trading where a computer program buys and sells desired articles after certain requirements are met. Since computers became more available, this kind of trading became more popular. The initial drops in stock prices led to further declines due to the program trading. For American Dow Jones Industrial Average, the 19th October still remains the biggest percentage change in history. In our data, this event can be observed for example on FTSE100 index for United Kingdom with Monday 19th being the second biggest decrease in our dataset and Tuesday 20th being the biggest decrease (10% and 12%, respectively).

In conclusion, the presented evidence do not appear as convincing when concerning negative returns. Although most of the estimates are indeed negative, around 65% of them. The underlying statistical significance does not provide much comfort. On the other hand, the outcome for the second part of Monday effect concerning lower returns on Monday than for the rest of the week as a whole is much more persuasive. Almost 85% of the estimates suggest lower Monday returns with decent supporting statistical significance (more than one third of all performed regressions). Interesting geographical pattern is detected, since indexes for Croatia, Cyprus and Greece were statistically significant and negative in both models. Therefore the best region to find present Monday effect from our chosen dataset is the Southeastern Europe.

Chapter 5

Conclusion

The seasonal effects on stock markets are interesting phenomena. Presence of seasonal patterns generates conflict with the Efficient Markets Hypothesis presented by Fama (1970). Persistence of seasonal pattern after its discovery would break the definition of "efficient markets" since the prices would not fully reflect all available information. In the case of weak form efficiency proposed by Fama (1970), which we take under scrutiny, the available information is represented by past prices. Considering our research is based on historical values of indexes, our analysis falls under the weak efficiency.

Contrary to the Efficient Market Hypothesis, several studies confirmed seasonal anomalies on stock markets—Kunkel *et al.* (2003), Jacobsen & Zhang (2014) or Moller & Zilca (2008). The seasonal effects researched in this thesis are January effect, Halloween effect, Turn-of-the-Month effect and Monday effect. These seasonal anomalies suggest lower or higher returns on stock in comparison between different seasons.

Motivated by previous research, we use Ordinary Least Squares regression with dummy variables for the evaluation of returns on stock for different seasonal periods, as did for example Cadsby & Ratner (1992) or Mehdian & Perry (2001). For the analysis we use 32 European stock indexes of national character.

What we can conclude from this analysis is that there are, indeed, still some seasonal patterns present on the European stock markets. To be specific, the results for January and Monday effects prove to be inconclusive and we are not able to confirm or disprove the possible presence of these seasonal anomalies on European stock markets. For January, we are unable to claim that the results for January are significantly different in comparison with other months or the rest of the year as a whole. Although the coefficients suggest positive returns on January, we are unable to safely claim that they are higher in comparison with other months due to the lack of almost any statistical significance (only 3 statistically significant results out of 32 indexes for each model). Similarly, in the case of Monday effect, the results are not significantly different enough from the rest of the week to confirm this seasonal pattern. Although the results from Model 1 (specified in Equation 4.6) do not confirm convincingly enough the negativity of Monday returns, the output from Model 2 (specified in Equation 4.7) does provide somewhat decent support (12 indexes being statistically significant at 10% level) for the claim about returns on Monday being lower than for the rest of the week.

On the other hand, the outcome for Turn-of-the-Month effect and Halloween effect is far more interesting. From the performed analysis, we are able to state that we have found enough evidence for the presence of both seasonal effects on European stock markets. The sign of coefficients suggest that returns for November through April are higher than for the rest of the year in most countries (29 out of 32 coefficients positive), although statistical significance provides support for 11 and 13 countries at 5% and 10% level, respectively. Unsurprisingly, the results suggest that the Halloween effect is not driven mainly by unusually high returns in January (which we failed to convincingly prove anyway) and thus is still present in its original form. The results from the analysis of January effect, where we compare returns from each month with January reveal more about Halloween effect. According to these results, the Halloween effect is more probably caused by worse performance in several of the "non-Halloween" months. As far as the Turn-of-the-Month goes, the anomaly is significant and observable throughout the whole Europe. We can prove this claim with the results where we find only one negative coefficient (statistically insignificant on top of that) and strong statistical significance of positive coefficients (20 out of 32 coefficients significant at 5% level). Moreover, we are able to find multiple members of every European subregion in the group of 11 countries, where the results are significant even at 1% level.

The contribution of this work lies in the use of up-to-date data with the focus aimed at European stock markets. The regional focused research is not usual in previous work done in this field, where the authors often focus on one country, one index or perform the analysis at global level without any regional focus. Also, the emphasis put on individual results and events with possible influence on the outcome is not so common. On the other hand, more profound analysis, for example with more accent given on the influential events and possible outliers related to them (due to some turbulent periods on the stock markets in recent past), could definitely shed some more light on the problematic of seasonal patterns on stock markets. Other direction in which the research might proceed would be development of profitable trading strategy based on confirmed seasonal patterns, similarly to Bouman & Jacobsen (2002).

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Appendix A

Appendix

Results of the regressions

Statistical software Stata was used for the analysis.[1]

The first column in the following tables for January effect represents results for the Model 1 (with dummies for each month excluding January) specified in Equation 4.1, i.e. results for intercept α. The second column represents results for Model 2 (with only one dummy for January) specified in Equation 4.2, i.e. results for coefficient δ.

The first column in the following tables for Halloween effect represents results for the original "Halloween" model (one dummy for the desired period) specified in Equation 4.3, i.e. results for coefficient δ. The second column represents results for the "Halloween" model adjusted for January (one dummy for the desired period, excluding January and one separate January dummy variable) specified in Equation 4.4 i.e. results for intercept α.

The letters in the brackets after the index name mark the procedure used for the estimation. O stands for OLS without any additions, R for heteroskedasticity robust errors, P for Prais-Winsten procedure and N for Newey-West standard errors.

Index, Location		January		Halloween	
AEX (R, O, R, O)	coefficient	-1.223	-1.266	1.030	1.379*
Netherlands	std. error	(1.314)	(1.390)	(0.785)	(0.820)
ATX (N, P, R, R)	coefficient	1.322	0.221	1.971***	2.014***
Austria	std. error	(1.315)	(1.220)	(0.709)	(0.721)
BEL 20 (N, P, P, N)	coefficient	-0.282	-0.968	1.159	1.368**
Belgium	std. error	(1.390)	(1.108)	(0.707)	(0.635)
BELEX 15 (N, P, P, P)	coefficient	2.397	1.190	0.935	0.840
Serbia	std. error	(2.390)	(2.335)	(1.903)	(1.920)

Table A.1: Summary results for January and Halloween effects

[1] Data and log files are enclosed to this thesis for possible reproduction of the results.

Index, Location		January		Halloween	
BET 10 (N, N, P, N)	coefficient	4.978	3.967	1.098	0.609
Romania	std. error	3.408	(3.393)	(1.459)	(1.401)
BUX (R, O, O, O)	coefficient	3.130	2.184	1.531	1.284
Hungary	std. error	(1.975)	(1.865)	(1.029)	(1.080)
CAC 40 (O, O, O, O)	coefficient	0.562	0.177	1.870***	2.024***
France	std. error	(1.050)	(1.121)	(0.610)	(0.641)
CROBEX (R, O, O, O)	coefficient	3.279	2.948	1.741	1.360
Croatia	std. error	(2.006)	(1.909)	(1.076)	(1.130)
DAX (O, O, R, O)	coefficient	0.392	-0.404	1.665**	1.907***
Germany	std. error	(1.145)	(1.228)	(0.682)	(0.713)
FTSE 100 (R, O, R, R)	coefficient	0.528	-0.038	1.182***	1.309***
United Kingdom	std. error	(0.891)	(0.811)	(0.450)	(0.452)
FTSE MIB (O, O, O, O)	coefficient	0.092	0.168	1.978**	2.148**
Italy	std. error	(1.404)	(1.485)	(0.825)	(0.867)
FTASE (O, O, O, O)	coefficient	0.678	1.115	1.172	1.086
Greece	std. error	(2.440)	(2.555)	1.402	1.472
FTSE/Cyse (R, P, P, P)	coefficient	3.014	5.010	0.189	-0.602
Cyprus	std. error	(3.336)	(3.052)	(1.983)	(2.042)
IBEX 35 (O, O, O, O)	coefficient	-0.351	-0.924	0.928	1.190
Spain	std. error	(1.400)	(1.453)	(0.802)	(0.841)
ISEQ Overall (P, P, P, P)	coefficient	0.767	-0.494	2.371***	2.540***
Ireland	std. error	(1.320)	(1.294)	(0.842)	(0.864)
MICEX 10 (P, P, P, P)	coefficient	2.335	-0.315	1.883	2.025
Russia	std. error	(2.325)	(2.301)	(1.436)	1.481
OBX (R, P, R, R)	coefficient	-1.225	-2.667*	1.365	1.907**
Norway	std. error	(1.625)	(1.541)	(0.905)	(0.916)
OMXC 20 (O, O, O, O)	coefficient	2.117*	1.239	1.345*	1.253*
Denmark	std. error	1.211	(1.258)	(0.691)	(0.726)
OMXH 25 (P, P, P, P)	coefficient	0.805	-0.448	1.983**	2.120**
Finland	std. error	(1.468)	(1.429)	(0.954)	(0.974)

Table A.2: Summary results for January and Halloween effects

Index, Location		January		Halloween	
OMXI 8 (R, O, O, O)	coefficient	2.104	1.371	0.215	-0.038
Iceland	std. error	(2.364)	(1.907)	(1.111)	(1.173)
OMXR (N, P, P, P)	coefficient	2.490	2.000	-0.518	-0.842
Latvia	std. error	(1.526)	(1.595)	(1.036)	(1.067)
OMXS 30 (O, O, O, O)	coefficient	0.385	-0.289	2.019***	2.274***
Sweden	std. error	(1.293)	(1.378)	(0.750)	(0.787)
OMXT (N, P, P, P)	coefficient	5.582**	3.976*	2.851**	2.400*
Estonia	std. error	(2.599)	(2.047)	(1.330)	(1.360)
OMXV (N, P, N, N)	coefficient	3.152**	2.600*	0.333	-0.084
Lithuania	std. error	(1.498)	(1.527)	(1.043)	(1.080)
PFTS (P, P, P, P)	coefficient	2.967	-1.240	5.374***	5.640***
Ukraine	std. error	(2.651)	(2.474)	(1.767)	(1.798)
PSI 20 (R, P, P, P)	coefficient	2.106	1.504	1.918**	1.790**
Portugal	std. error	(1.470)	(1.363)	(0.842)	(0.867)
PX (O, O, O, O)	coefficient	1.303	0.880	1.464*	1.449
Czech Republic	std. error	(1.469)	(1.549)	(0.851)	(0.895)
SAX (R, O, R, O)	coefficient	-0.872	-1.385	0.159	0.429
Slovakia	std. error	(1.357)	(1.377)	(0.763)	(0.799)
SBI TOP (P, P, P, P)	coefficient	2.088	2.998*	0.014	-0.305
Slovenia	std. error	(1.885)	(1.659)	(1.247)	(1.258)
SMI (P, P, P, P)	coefficient	-0.118	-0.943	0.727	0.923
Switzerland	std. error	(0.864)	(0.877)	(0.549)	(0.564)
SOFIX (N, P, P, P)	coefficient	2.341	0.110	-0.0006	-0.016
Bulgaria	std. error	(2.756)	(2.217)	(1.514)	(1.548)
WIG 30 (O, O, O, O)	coefficient	-1.950	-1.632	-0.664	-0.391
Poland	std. error	(1.783)	(1.969)	(1.204)	(1.277)

Table A.3: Summary results for January and Halloween effects

* marks statistical significance at 10% level

** marks statistical significance at 5% level

*** marks statistical significance at 1% level

The first column represents the model with only one dummy variable for Monday effect specified in Equation 4.7, i.e. results for coefficient δ. The second column in the following tables for Monday effect represents the model with binary variables for every workday excluding Monday, specified in Equation 4.6, i.e. results for intercept α.

Index, Location		Monday		Turn of the month
AEX (R, R, O)	coefficient	-0.014	-0.006	0.107*
Netherlands	std. error	(0.063)	(0.058)	(0.057)
ATX (N, N, P)	coefficient	-0.026	0.007	0.166***
Austria	std. error	(0.049)	(0.045)	(0.047)
BEL 20 (N, N, P)	coefficient	-0.0103	0.013	0.138***
Belgium	std. error	(0.048)	(0.044)	(.047)
BELEX 15 (N, N, N)	coefficient	-0.115*	-0.104	0.051
Serbia	std. error	(0.067)	(0.064)	(.067)
BET 10 (N, N, P)	coefficient	-0.113*	-0.036	0.197***
Romania	std. error	(0.065)	(0.060)	(0.070)
BUX (R, R, R)	coefficient	0.140**	0.174***	0.242***
Hungary	std. error	(0.065)	0.059	(0.060)
CAC 40 (R, R, O)	coefficient	-0.062	-0.027	0.093**
France	std. error	(.048)	(0.044)	(0.044)
CROBEX (P, R, R)	coefficient	-0.168***	-0.115**	0.128**
Croatia	std. error	(0.058)	(0.053)	(0.059)
DAX (R, R, O)	coefficient	-0.062	0.066	0.117**
Germany	std. error	(0.048)	(0.046)	(0.046)
FTSE 100 (R, R, O)	coefficient	-0.072**	-0.031	0.098***
United Kingdom	std. error	(0.032)	(0.029)	(0.030)
FTSE MIB (R, R, O)	coefficient	-0.093	-0.069	0.206**
Italy	std. error	(0.064)	(0.059)	(0.105)
FTASE (R, R, P)	coefficient	-0.242***	-0.206***	0.244***
Greece	std. error	(0.086)	(0.078)	(0.087)
FTSE/Cyse (N, N, P)	coefficient	-0.320***	-0.321***	0.081
Cyprus	std. error	(0.108)	(0.100)	(0.059)
IBEX 35 (R, R, O)	coefficient	-0.099*	-0.051	0.114**
Spain	std. error	(0.057)	(0.052)	(0.054)
ISEQ Overall (N, N, R)	coefficient	-0.099*	-0.058	0.257***
Ireland	std. error	(0.053)	(0.046)	(0.053)
MICEX 10 (R, R, R)	coefficient	0.076	0.174**	0.192**
Russia	std. error	(0.097)	(0.085)	(0.094)

Table A.4: Summary results for Turn-of-the-Month and Monday effects

Index, Location		Monday		Turn of the month
OBX (R, R, O)	coefficient	-0.068	-0.010	0.161***
Norway	std. error	(0.067)	(0.061)	(0.062)
OMXC 20 (R, R, P)	coefficient	0.026	0.072	0.160***
Denmark	std. error	(0.049)	(0.045)	(0.047)
OMXH 25 (R, R, R)	coefficient	-0.009	0.036	0.118**
Finland	std. error	(0.058)	(0.052)	(0.058)
OMXI 8 (N, N, N)	coefficient	-0.181**	-0.103	0.057
Iceland	std. error	(0.092)	(0.089)	(.059)
OMXR (P, R, O)	coefficient	-0.184***	-0.092*	-0.044
Latvia	std. error	(0.058)	(0.054)	(.058)
OMXS 30 (R, R, O)	coefficient	0.072	0.096*	0.110**
Sweden	std. error	(0.058)	(0.053)	(0.055)
OMXT (N, N, N)	coefficient	-0.089	-0.015	0.088
Estonia	std. error	(0.059)	(0.056)	(0.058)
OMXV (N, N, P)	coefficient	-0.096**	-0.032	0.031
Lithuania	std. error	(0.046)	(0.044)	(0.043)
PFTS (R, R, R)	coefficient	0.169	0.187	0.123
Ukraine	std. error	(0.125)	(0.118)	(0.089)
PSI 20 (N, N, P)	coefficient	-0.037	-0.020	0.140***
Portugal	std. error	(0.045)	(0.041)	(0.047)
PX (P, P, N)	coefficient	-0.002	0.017	0.093*
Czech Republic	std. error	(0.048)	(0.044)	(0.050)
SAX (P, N, N)	coefficient	-0.051	-0.022	0.042
Slovakia	std. error	(0.048)	(0.044)	(0.047)
SBI TOP (P, P, N)	coefficient	-0.107*	-0.099*	0.130**
Slovenia	std. error	(0.056)	(0.053)	(0.058)
SMI (R, R, P)	coefficient	-0.028	0.012	0.103***
Switzerland	std. error	(0.040)	(.037)	(0.038)
SOFIX (O, R, O)	coefficient	-0.100	-0.026	0.039
Bulgaria	std. error	(0.065)	(0.057)	(0.065)
WIG 30 (R, R, R)	coefficient	-0.051	-0.066	0.009
Poland	std. error	(0.100)	(0.092)	(0.101)

Table A.5: Summary results for Turn-of-the-Month and Monday effects

Short characteristics of the indexes[2]

AEX (Amsterdam Exchange Index) is market capitalization weighted index from NYSE Euronext Amsterdam, Netherlands. It consists of 25 leading stocks traded on the market. Starting in January 1999, we have 4386 daily and 206 monthly observations.

ATX (Austrian Traded Index) is capitalization weighted index from Vienna Stock Exchange, Austria. Presently, it consists of 20 most traded stock on the market. Starting from November 1992, we have 5773 daily and 280 monthly observations.

BEL 20 (Belgium) is Euronext Brussels' capitalization weighted index. Currently, it consists of 20 stocks with highest capitalization and liquidity on the market. Starting from March 1996, we have 5080 daily and 540 monthly observations.

BELEX 15 (Belgrade Stock Exchange) is market capitalization weighted index from Serbia and is composed of 15 blue-chip stock from the market. Starting in October 2005, we used 2620 daily and 125 monthly observations.

BET 10 (Bucharest Exchange Trading) is free-float capitalization weighted index from Bucharest, Romania and is composed of 10 most liquid stock traded on the market. Starting from September 1997, we acquired 4604 daily and 222 monthly observations.

BUX (Budapest Stock Exchange) is free-float capitalisation weighted index from Hungary. It consists of 15 blue-chip stock. Our dataset includes 4977 daily and 240 monthly observations beginning from March 1996.

CAC 40 (Cotation Assistée en Continu) is Euronext Paris' capitalization weighted index. It is composed of 40 largest stock listed on the stock exchange and it is often used as a benchmark for the Paris' market. Used dataset begins in March 1990 and has 6590 daily and 312 monthly observations.

CROBEX is free-float market capitalization weighted index for Zagreb Stock Exchange, Croatia. It consists of 25 most traded and highest free-float market capitalization shares on the stock exchange. Our dataset begins in January 1998 and contains 4430 daily and 218 monthly observations.

DAX (Deutscher Aktienindex) is blue-chip index for Germany's Frankfurt Stock Exchange. It consists of 30 most important listings. Starting with November 1990 the dataset includes 6396 daily and 304 monthly values.

FTSE 100 (Financial Times Stock Exchange 100) is free-float market capitalization stock index for London Stock Exchange consisting of 100 listings with highest market capitalization. Starting from January 1984, our dataset contains 8374 daily and 386 monthly observations.

FTSE MIB (Milano Italia Borsa) is benchmark stock index for Borsa Italiana in Milan. It is composed of 40 most capitalized and liquid shares on the market. Used dataset contains 4655 daily and 219 monthly observations starting from January 1998.

FTASE is Greek share index for Athens Stock Exchange and consists of most capitalized and liquid shares on the market. Starting from October 1997 and ending at the end of 2015 (the only dataset not ending in February 2016), we have 4684 daily and 219 monthly observations.

FTSE/CYSE is capitalisation weighted stock index from Cyprus Stock Exchange. It

[2]The datasets were obtained from finance.yahoo.com and Thomson Reuters Eikon - Wealth Management database.

comprises 20 most liquid and largest listings on the stock exchange. Our dataset begins in December 2000 and has 3743 daily and 183 monthly observations.

IBEX 35 (Índice Bursátil Español) is Spanish free-float capitalisation weighted index for Madrid stock exchange. It contains 35 most liquid listings. Used dataset starts in March 1996 and has 5042 daily and 240 monthly values.

ISEQ Overall (Irish Stock Exchange) is capitalisation weighted index from Dublins' stock exchange. Our dataset begins in July 1997 and contains 4724 daily and 224 monthly values.

MICEX 10 (Moscow Interbank Currency Exchange was one of two merging entities from which Moscow Exchange was established) is Russian stock index for Moscow Exchange. It is composed of 10 most liquid listings. Used dataset begins in March 2001 and consists of 3732 daily and 180 monthly observations.

OBX (Oslo Børs index) is free-float adjusted stock index for Oslo Stock Exchange in Norway. It contains 25 most traded securities on the market. Starting from September 1999, the dataset includes 4138 daily and 198 monthly observations.

The OMX Copenhagen 20 (OMXC 20) is free-float market capitalisation share index for Denmarks' Copenhagen Stock Exchange, part of OMX Nasdaq Group. It is composed of 20 most traded securities of the 25 most capitalised stock on the market. Our dataset contains 4994 daily and 240 monthly observations since March 1996.

The OMX Helsinki 25 (OMXH 25) is Finnish capitalisation weighted index for Helsinki Stock Exchange, part of OMX Nasdaq Group. It includes 25 most traded listings on the market. Used dataset has 4996 daily and 240 monthly observations since March 1996.

The OMX Iceland 8 (OMXI 8) is Icelands' share index consisting of 8 major stock on the market. Is is the successor of OMXI15 and OMXI6 as the benchmark index for Nasdaq OMX Iceland. It is operated by OMX Nasdaq Group. Our data begin in January 2009 with 1780 daily and 86 monthly observations.

The OMX Riga (OMXR) is Latvian all-share index. It is the benchmark index for Riga Stock Exchange, part of the OMX Nasdaq Group. Acquired dataset starts in January 2000 and has 4006 daily and 194 monthly observations.

The OMX Stockholm 30 (OMXS 30) is Swedens' capitalisation weighted index for Stockholm Stock Exchange, part of OMX Nasdaq Group. It contains 30 most traded securities on market. Our data begins in March 1996 and has 5004 daily and 240 monthly observations.

The OMX Tallinn (OMXT) is Estonian share index that contains every stock listed on the Tallinn stock exchange, part of the OMX Nasdaq Group. Our data begins in June 1996 and has 4978 daily and 237 monthly values.

The OMX Vilnius (OMXV) is Lithuanian stock index including again all of the listed shares on the Vilnius Stock Exchange, part of the OMX Nasdaq Group. Used data begins in January 2000 and contains 3993 daily and 194 monthly observations.

PFTS index is Ukrainian capitalisation weighted share index, which is composed of 20 leading stock traded on PFTS Ukraine Stock Exchange. Beginning from October 1997, the dataset contains 4403 daily and 221 monthly values.

PSI 20 (Portuguese Stock Index) is free-float capitalization weighted index for Euronext Lisbon. The index is composed of 20 largest stock on the market. Used dataset begins in March 1996 and contains 5133 daily and 240 monthly observations.

PX is official capitalisation weighted share index of Prague Stock Exchange. It is successor of PX-50 and PX-D indices and contains 12 major stock on the market. Our data begins in March 1996 and contains 5005 daily and 240 monthly observations.

SAX(Slovenský Akciový Index) is capitalisation weighted stock index from Bratislava Stock exchange. Our dataset begins in March 1996 and contains 4773 daily and 240 monthly observations.

SBI TOP is Slovenian free-float capitalisation weighted index for Ljubljana Stock Exchange. It includes most traded blue-chip shares. The dataset begins in April 2006 and has 2466 daily and 119 monthly observations.

SMI (Swiss Market Index) is blue-chip share index for SIX Swiss Exchange. It is composed of 20 most traded and largest stock listed on the stock SIX Swiss Exchange. Used dataset begins in November 1990 and includes 6391 daily and 304 monthly values.

SOFIX is free-float market capitalisation weighted index for the Bulgarian Stock Exchange and is composed of the largest and most traded securities on the market. It started as the first index on the Bulgarian Stock Exchange. Beginning in October 2000, we acquired 3808 daily and 185 monthly observations.

WIG 30 is Polish capitalisation weighted stock market index. It is composed of 30 largest companies listed on the Warsaw Stock Exchange. Used dataset begins in January 2013 and contains only 787 daily and 39 monthly observations.