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Analysis of stock market anomalies: US cross-sectoral comparison

Bachelor thesis

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Abstrakt

Tato práce zkoumá anomálie ve výnosech akcií na finančních trzích ve Spojených státech. Speciální důraz je kladen na Efekt dne v týdnu, Lednový efekt a Efekt dnů v měsíci. Zaměříme se na porovnání společností s malou a velkou tržní kapitalizací. Provedeme analýzu napříč 6 průmyslovými sektory. Jednotlivé výsledky porovnáme s výsledky předchozích studií. Na závěr se pokusíme stanovit spekulativní investiční strategii. Zjistili jsme, že ani Efekt dne v týdnu, ani Lednový efekt se na americkém trhu v současné době nevyskytuje. Jedinou pozorovanou anomálií je Efekt dnů v měsíci.

Klíčová slova

Anomálie ve výnosech akcií, finanční trhy, sektorální analýza, Lednový efekt, Efekt dne v týdnu, Efekt dnů v měsíci

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Abstract

The purpose of this thesis is to analyze anomalies in the US stock market. Special attention is put on Day of the week effect, January effect, and Part of the month effect. We focus on comparison of companies with low and high capitalization. We perform an analysis across 6 major industrial sectors. Then, we discuss the findings with results of past projects and finally, we try to find a speculative investment strategy. We found out that neither Day of the week effect nor January effect do not appear in US stock market nowadays. Part of the month effect was the only anomaly, which was observed in our data.

Keywords

Stock market anomalies, financial markets, cross-sectoral analysis, Jannuary effect, Day of the week effect, Part of the month effect

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Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, May 17, 2012

Signature

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I would like to express my gratitude to PhDr. Ladislav Krištoufek for valuable suggestions and support while writing my bachelor thesis.

Project of Bachelor Thesis

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US cross-sectoral comparison

Goals of the thesis:

The aim of this bachelor thesis is to verify the efficiency of American stock market and confirm the presence of major calendar anomalies - Day of the week effect, January effect, and Monthly effect. Then, we focus on comparison of low and highly capitalized companies. This thesis is unique in unusual approach to calendar anomalies, specifically in the examination of anomalies across industrial sectors. Finally, we try to determine the investment strategy.

Synopsis:

1. Literature review
2. Data description
3. Methodology
4. Empirical results and discussion

References:

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Contents

Introduction

The global financial crisis burst out in the United States 5 years ago. It consequently affected *global stock markets* and many companies went bankrupt. Some stock markets even collapsed. Until now nobody wants to invest their money in stocks with expectant low returns and high risk. In the crises like this, various anomalies in stock markets appear more frequently. "Is *efficient market hypothesis* still valid?", question which every investor asks.

Efficient market hypothesis is one of the most discussed topic of recent years. It was originally proposed by Samuelson (1965) and Fama (1965) as far back as the 1960s. The hypothesis states that stock market is efficient if information spreads very quickly and is immediately incorporated into the stock prices. Therefore, stocks are traded for *fair value*. It is impossible to buy undervalued or to sell overvalued stocks. Randomly chosen portfolio of stocks is expected to have the same desired return as a portfolio of stocks which is properly chosen using a fundamental or technical analysis,(Malkiel, 2003 and Malkiel, 2005).

The efficient market hypothesis was widely accepted in the middle of the 20^{th} century. However, lately it was found that stocks are not traded for fair values and that some patterns in stock yield exist, (Jensen, 1978). Anomalies in stock returns were found in American, European, and Australian market and the theory of efficient market hypothesis was damaged,(Jaffe and Westerfield, 1985).

Malkiel (2003) claimed that market could be efficient, despite the fact that some periods of time when fundamental or technical analysis can never be implemented, exist. Sometimes people behave irrationally and make outrageous mistakes as in Internet bubble in 1999, when investors were buying 10 times overvalued stocks. Such "bubbles" certainly exists but they are believed to be an exception rather than a rule. Nevertheless what is usually meant by the term *efficient markets*?

This problem is nicely illustrated in a commonly-told story about a financial professor and his student. The professor and his student walked on the street and came across a one hundred bill lying on the ground and the student wanted to pick it up. The professor stopped him and said: "Do not bother if it was a real one hundred bill someone would have definitely picked it up before you." Whenever pattern is discovered it is expected to last a for short time. Therefore, it can never be implemented in the market. Every investment strategy, which emerges to the surface, is immediately spread among investors all over the world, receives its publicity, and thus investors cannot gain extraordinary returns.

Most stock anomalies can be determined only by a retrospective *data mining*[1], (Sullivan, Timmermann, and White 2001). It is very likely that if we get some data we can always find a pattern, which could have been implemented into the trading strategy in past. This trading strategy would have been effective in past but unfortunately it cannot be used for the future, Malkiel (2003). Once the pattern obtains its publicity, investors try to profit from the knowledge and apply it on the markets. As a result, the pattern self-destructs very rapidly. In the age of internet and television we should not be surprised that stock anomalies do not exist or survive for a long time, (Marquering, Nisser, and Valla, 2006).

An example of January effect[2] demonstrates well the phenomenon. Researchers discovered that the January effect in the American stock markets in the 20th century was particularly significant for small companies. These companies generated exceptionally high returns during the first five days in January. In such situation investors would buy the stocks at the end of December and sell them on the fifth day of January. After a while they would have found out that all of them had implied the same strategy. Trading volumes would have been especially high these days and the profit would have been lowered. Investors would have had to react because they had not generated so much profit. Consequently, they would start to buy one day before the end of December and sell on the 4th of January in order to take advantage of the January effect. To beat the market and the knowledge of others, the investors would buy earlier and earlier in December and sell earlier and earlier in January and

[1] Data mining = extraction of useful information from data; Witten, Frank, Hall (2011)

[2] January effect is a calendar pattern in stock returns. It says that the highest returns in the year occur in January, Thaler (1987).

January effect would finally disappear, (Malkiel, 2003).

Anomalies in stock markets were a hot topic during 80s and 90s. A lot of stock patterns have been examined so far, e.g. *Day of the week effect, January effect, Part of the month effect, or Turn of the year effect.* It has been found that along with development of information technologies some anomalies disappear while new ones arise. A lot of researchers devote their career to analysis of possible causes of the anomalies. Nevertheless, nobody has found the answer, why the returns are higher in some days and months than in other ones. Hence, most researchers agree that psychological effects play the key role.

The aim of the bachelor thesis is to *prove the presence of anomalies in U.S. stock market* during last years. We use all available methods and try to determine a speculative financial strategy. We focus on differences between low and highly capitalized companies. The uniqueness of this thesis lies in unusual approach to calendar anomalies, specifically in the examination of anomalies across the industrial sectors.

The bachelor thesis is organized in the following manner. First, we review empirical findings of other researchers. We look in detail at Day of the week, January, and Part of the month effect. Other anomalies are also briefly mentioned in order to attain the completeness of the review. Second, we statistically describe data, compare results for low and highly capitalized companies and different sectors such as Financial, Health Care, Industrial, Oil & Gas, Technology, and Telecommunications. Then, we propose our model for testing the above-mentioned anomalies. Finally, we show the empirical results and comment the findings for Day of the week, January, and Part of the month effect.

1 Anomalies in stock returns

Anomalies in stock returns are abnormalities in behavior of stocks on the markets. Anomalies are not only connected with price but also with stock volume traded in the markets. According to efficient market hypothesis average monthly or daily expected returns should be identical for the whole year. There is no reason why average returns in January should be higher than average returns in July. All that said, reality is different and researchers found anomalies in all stock markets around the world. To the most discussed anomalies belong Day of the week effect[3] or January effect however we must not forget to mention Part of the month or Holiday effect. A literature review of the mentioned anomalies follows in chronological manner.

1.1 Day of the week effect

In the 1970s and the 1980s empirical works concerning stock returns started to increase rapidly. Initially, a conjecture of the same stock returns in all days of the week prevailed. Later, beliefs of an effect of a weekend started to appear. One of the first researchers who began to investigate the stock returns was Fama (1965), who discovered a 20% higher variance in stock returns on Monday compared to other days. Godfrey, Granger, and Morgenstern (1964) reached the same conclusion using other method of computation and one decade later Cross (1973) and French (1980) found an evidence of negative returns on Monday.

Gibbons and Hess (1981) were the first researchers who examined the Monday effect in more details and tried to reveal the causes. Empirical study "Day of the week effect and Asset Returns" from Michael Gibbons and Patrick Hess not only confirmed previous studies of Cross (1973) and French (1980) about negative stock returns on Monday, but also found a below-average return for treasury bills. They conducted tests using S&P 500[4] on data from February 1962 to December 1978. Whereas negative returns of the sample on Monday proved the Day of the

[3] Day of the week effect is sometimes called Monday effect or Weekend effect

[4] S&P 500 = 'Standard & Poor's 500 Index

week effect, sample variance did not. Monday was the only day with negative returns. Variance was indeed highest on Monday, but the difference from Wednesday or Tuesday was insignificant. Gibbons and Hess (1981) tested the hypothesis of the identical distribution for returns for all days from Monday to Friday. Using assumption of an equality of all regression coefficients they came to the conclusion that hypothesis of identical distribution of stock returns had to be rejected. This result definitively damaged the assumption from 70s concerning the same returns during a week.

Since the causes of negative returns on Monday remained unclear, Gibbons and Hess (1981) tried to clean the data from heteroskedasticity, which had already been found by Godfrey, Granger and Morgenstern (1964) using standardized estimates for each day. Nevertheless, results for weighted and non-weighted equations were almost identical.

Gibbons and Hess (1981) tried to explain the Monday effect in more details. They intentionally did not use data before February 1968 because a settlement period was only 4 days until that time. For the reason of time difference between the day when stocks are quoted and the day when transaction is settled, spot[5] prices differ from forward[6] prices . The price was grossed up only by 4 days of interest on Monday and in other days by 6 days of interest before 1962. The situation changed after 1962 when the settlement periods were harmonized for 6 days. Interestingly, Monday effect was found before 1962 as well. Consequently, Gibbons and Hess (1981) tried to test an impact of different settlement procedures using mean adjusted forms of equations. As expected, they claimed that different settlement period does not resolve the Monday effect.

Since the settlement period played no role for explaining Monday effect, Gibbons and Hess (1981) tried to include measurement errors - upwardly biased prices on Friday and downwardly biased prices on Monday. They used the hypothesis of an offsetting effect with a result of rejection on all significance levels. Some explana-

[5]Spot price = current price at which it is possible to buy/sell shares on the market;Cox, Ingersoll and Ross (1981)

[6]Forward price = value at time t of a contract which will pay at time s the amount, Cox, Ingersoll and Ross (1981)

tions were suggested, but neither of them helped to justify the Day of the week effect.

Keim and Stambaugh (1984) continued the work of Gibbons and Hess (1981). They extended the examination period for 55 years and tried to find additional pieces of information about the Monday effect. New York Stock Exchange was opened 6 days a week until 1952 and Saturday was the last trading day of the week that time. This fact had to be projected in daily returns. Within 25 years from 1928 to 1952 when NYSE[7] closed on Saturday, Friday's returns were not the highest of the week. On the contrary, Friday had the second lowest returns of the week (after Monday). The highest returns were attributed to Saturday. Thus, Keim and Stambaugh (1984) tested a hypothesis that average returs on Friday in a week with one non-trading day equals the rate of return in a week with two non-trading days. This hypothesis was rejected on all significance levels which indicated that last trading day in a week had the highest return.

Keim and Stambaugh became famous particularly because of their finding that daily returns were affected by the firm's size. Using NYSE and AMEX[8], 1963 - 1979 they constructed firm's size deciles according to their market capitalizations. The returns on Monday were significantly negative for all market-value portfolios and the hypothesis of equal returns for Monday across all market-value portfolios was rejected. The smallest size decile showed the largest both Friday's returns and Monday's returns and indicated that power of the Day of the week effect was somehow correlated with size of the portfolio. Day of the week effect was the strongest for firms belonging to the small size decile and the weakest for firms belonging to the large size decile. Just like Gibbons and Hess (1981), Keim and Staumbaugh (1984) tried to explain the Monday effect by a measurement error. Although the hypothesis that Monday's returns offset Friday's returns could not be rejected for each size portfolio, the hypothesis was jointly rejected for all deciles together which failed to support the explanation of Monday effect.

Keim and Staumbaugh (1984) also attempted to clarify the causes of Monday

[7] NYSE = New York Stock Exchange

[8] AMEX = American Stock Exchange

effect by bid[9]-ask[10] spread, but the evidence presented in the study indicated that Monday effect was not affected by systematic difference between bid and ask prices.

Another milestone in examining stock anomalies was a study of Prince (1982), who decomposed the weekend effect into two main parts: non-trading effect from Friday close to Monday open and trading effect from Monday open to Monday close. He used DJIA[11] data for five-year period and claimed that Monday effect occured during trading time[12] from Monday open to Monday close.

Rogalski (1984) continued in examining intraday data and found interesting evidences. First, Monday returns were not negative because of trading effect, but because of non-trading weekend effect. Data from 1974 to 1984 showed that mean returns for non-trading period were negative and the hypothesis of equal daily returns was rejected on all significance levels. Furthermore, Monday returns on trading day[13] were surprisingly positive and the hypothesis of equal returns could not be rejected.

Second, Rogaski (1984) linked the Monday effect to January effect and showed that Monday returns were surprisingly positive in January but negative in other months of the year. The result of positive Monday returns in January was attributed to significantly higher returns for trading day, which prevailed in the non-trading period. He also extended the study of Keim and Staumbaugh (1981) and tried to examine the Day of the week effect and January effect across different market-value portfolios. Regardless of the day of the week small firms achieved higher returns in January than large firms. Furthermore, the hypothesis of equal returns for all days of the week could not be rejected on 1% level of significance.

[9]Bid price = price at which the specialist fills a limit buy order, Source: Keim, Staumbaugh (1983)

[10]Ask price = price at which the specialist fills a limit sell order, Source: Keim, Staumbaugh (1983)

[11]DJIA = Dow Jones Industrial Average

[12]Trading time = time when stock exchange is open

[13]Trading day = part of the day when stocks are traded

Smirlock and Starks (1986) noticed the instability in timing of the weekend effect provided by Prince (1982) and Rogalski (1984). Thus, they extended the examination period for 20 years in order to bring an additional point of view on Monday effect, particularly timing, and nature of the anomaly. They divided data into three subperiods and reported that although weekend effect occurred before 1974 from Friday close to Monday open, the period after 1974 was characterized by returns which occurred from Monday open to Monday close. This evidence confirmed findings of Rogalski (1984). Whereas the hypothesis of equality of daily close to open returns was rejected for both subperiods before 1974, the hypothesis of equality of daily open to close returns could not be rejected on five percent level of significance. These evidences suggested a time shift of Day of the week effect.

Smirlock and Starks (1986) also tried to examine the intraday patterns. They discovered that returns are lower on Monday morning than their counterparts on other days of the week. This result did not bring anything special but confirmed the conjecture that effect of weekends was not stable in time.

Day of the week effect was primarily examined for US stock market. Thus, Jaffe and Westerfield (1985) studied if the Day of the week effect is a worldwide phenomenon or a consequence of institutional arrangements in the United States. They used data for Australian, Japanese, Canadian and British market and stated an evidence of significant negative returns on Monday and positive returns on Friday. Interestingly, Monday returns were not the lowest for Japanese and Australian stock exchange because Tuesday returns were even more negative.

Two explanations were suggested. Different time zones and correlation between American and domestic market or, inspired by Gibbons and Hess (1981), measurement errors and settlement period. Nevertheless, neither of these clarified the causes of Day of the week effect.

Causes of Day of the week effect remained unclear and many attempts for its explanation were done. Solnik and Busquet (1990) use other market than Gibbons and Hess (1981) or Jaffe and Westerfield (1985) - namely Paris bourse and wanted to examine the causes of a settlement period on this forward market. French market provided a good opportunity to test the importance of a specific French settlement period in stock returns. Interestingly, Solnik and Busquet (1990) gave evidence that this specific settlement procedure did explain high returns on Friday.

Berument and Kyimaz (2001) focused on the relationship between returns and volatility. They observed the highest returns on Wednesday and the lowest on Monday. On the other hand, the highest standard occurred on Friday and the lowest on Wednesday. Berument and Kyimaz (2001) tried to explain the Friday's highest volatility. One explanation was suggested. Bad news, which often release on weekends, could influence the behavior of investors.

G. Kohers, N. Kohers, Pandey, and T. Kohers (2004) noted that market efficiency has been steadily increasing. Thus, they tested whether the improvement in market efficiency has some impact on the presence of the Day of the week effect in equity markets in the world. Using period from 1980 - 2002 they found out that the Day of the week effect almost disappeared and is definitely not as common as in the 1980s.

Berument and Dogan (2010) continued the work of Berument and Kyimaz (2001) and examined the connection between volatility and returns. They employed EGARCH model and lengthened the examination period for 1952 - 2006. The highest returns were either on Wednesday or on Friday, the lowest returns occured on Monday. Unlike Berument and Kyimaz (2001), they found the highest volatility not on Friday but on Monday. Interestingly, Friday had the lowest standard deviation in the week.

The Weekend effect is not as common as in the 70s or the 80s today. In spite of this, it can still be found in some markets. No satisfactory explanation has been provided so far and more and more researchers incline to psychological causes of the Day of the week effect.

1.2 January effect

Another and not less notable pattern in stock returns is January effect. Rozeff and Kinney (1976) began examining the stock market anomalies related to months in the year. They documented significantly higher returns in January than in other months. Keim (1983) resumes of Rozeff and Kinney's (1976) work and demonstrated a relation between market size portfolios and January effect. Using data from 1963-1979 across NYSE and AMEX he observed a negative relation between size of a company and risk adjusted returns. He suspected that this negative relation was caused by the fact that OLS betas[14] estimates could have been biased and therefore he computed adjusted betas[15]. For all that, Keim observed still negative relation between firm size and risk adjusted returns with the adjusted betas. He also pronounced another interesting finding - almost 50 percent of yearly company returns were accrued in January and moreover, more than 50 percent of Turn of the year effect was due to exceptionally large returns during first week of trading.

Further, Roll (1983) confirmed findings of Keim (1983) using data from 1962 - 1980 and demonstrated that January was the only month with abnormal premium for small firms. He also noted that last trading day in December and first four trading days in January are the days with the highest returns. Daily returns in this small period of time at turn of the year exceeded other days of the year by more than 100 percent.

Reinganum (1983) agreed with Keim (1983) and Roll (1983) about higher profits of small firms in the beginning of January. However, his study was more important in a different aspect. He tried to connect the tax-loss selling hypothesis with size portfolios. Thus, he divided firms into 40 groups according to their market value (MV1 - MV10) and according to the tax-loss selling measure (T1 - T4)[16]. Potential

[14]Beta = measure of the volatility, used to generate a security's expected rate of return for discounting cash flows, and to compute risk-adjusted returns; Chan,Lakonishok (1992)

[15]Betas were adjusted for non-synchronous trading and infrequencies intrading

[16]Calculation: the price of a stock on the second to the last trading day in December divided by the maximum price during last 6 months.

candidates for tax-loss selling were firms with lowest ratio (T1). He observed that more than 60 percent of firms with the smallest market value were included in T1 group and more than 40 percent of large firms were in upper quartile (T4). Thus, he suggested that tax-loss selling hypothesis could be partly correlated with market value.

Indeed, Reinganum (1983) found that companies with largest price declines exhibited highest returns during first days in January. This indicated that at least a part of the January effect could be described by tax-loss selling hypothesis[17]. However regardless of extreme profits within the first five days in January explained by tax-loss selling hypothesis, small firms had higher returns throughout the whole January. This affected the conclusion made by Reinganum (1983). "Despite tax loss selling hypothesis could clarify high returns at the beginning of January this hypothesis could not explain the entire January effect." Reinganum (1983) also noted one interesting fact: even if the investor would have known this pattern in advance he could not have gained extra profit due to transaction costs.

Australia has a different tax year starting in July and ending in June. So Brown, Keim, Kleidon and Marsch (1983) tried to implement the tax-loss selling hypothesis in this market and decide, whether tax-loss selling caused higher returns at the beginning of a new tax year. They illustrated interesting finding. Although the tax-loss selling hypothesis predicted the highest returns on July, market results showed something else. Returns in January were still significantly higher than in other months with exception of the four smallest portfolios in July. Brown, Keim, Kleiden and Marsch (1983) therefore concluded that there was no causal effect of tax-loss selling hypothesis on monthly returns.

Due to the lack of proper explanation of January effect Jones, Pearce and Wilson (1987) reinvestigated the tax-loss selling hypothesis. They used data for longest available period and divided it into two parts - before and after 1917. Year 1917 was

[17] Tax-loss selling = buying the stocks of companies, which achieved the lowest prices in the year during the last week of December and then selling these stocks in January,Branch (1977).

a breakpoint in the period because the tax on firm profits was enacted in the same year. The aim of their research was to show, whether this tax-act played a significant role in explanation of the January effect. Using the same estimator[18] as Gallant (1987) Jones, Pierce and Wilson (1987) were not able to reject the joint hypothesis of no seasonality neither for period from 1897 - 1917 nor for period from 1918 - 1938. They also tested the hypothesis of identical coefficients for both periods but it could not be rejected on 5 percent level of significance. Finally, they concluded that there was no significant change in returns before and after the enactment of the tax-law.

Seyhun (1987) extended the work of Glosten and Milgrom (1985) and developed more advanced tests about a relation between insider trading[19] and causes of January effect. Seyhun (1987) noted that inside traders knew the unpublished information about their company and therefore their behavior could influence the returns at turn of the year. He examined two possible causes of January effect: Compensation for increased risk of trading against inside traders and price pressure caused by changes in demand made by informed traders, who could possibly influence returns in January. Although the data showed that informed traders accelerated their purchases for December and deferred sales for second half of January, other findings were not so supportive. The results showed that inside traders increased neither purchases, nor the whole trading activity during January. Thus, Seyhun (1987) concluded that there was no causal effect of insider trading on January effect.

Haugen and Jorion (1996) examined the relation between January effect and market capitalization of companies. Using New York Stock Exchange data they examined the period from 1926 to 1993. They observed that January effect was still present in the data. However, the difference between January returns and returns in other months diminished in time.

[18]Gallant's estimator = generalized White's heteroskedasticity consistent estimator

[19]Insider tading = trading by informed traders, who are likely possess to non-public information, Seyhun (1987).

Choudry (2001) was another researcher, who tested January effect. He analyzed data from 1871 to 1913 for American, British, and German markets. Using moving average process together with GARCH model, he found that summer months, October, and November produced low returns. On the contrary, January was characterized by the highest returns in the year. Finally, he concluded that January effect was present in the data and was very significant.

Moller and Zilca (2007) continued the work of Haugen and Jorion (1996) and were interested in the connection between the January pattern in stock returns and firm size. They examined data of NASDAQ, AMEX, and NYSE for period from 1927 to 2004. The results did not differ from previous findings of other authors. Moller and Zilca (2007) observed high returns in January, which were exceptionally high for small companies. On the other hand, the lowest returns occurred in September and October. After a detailed analysis, they concluded that higher market capitalization of companies is accompanied by lower returns.

No explanation, which would entirely clarify the causes of January effect has been illustrated so far. Tax-loss selling hypothesis could partly justify some patterns in stock returns - (Brown, Keim, Kleidon, and Marsch, 1983) - but the entire January effect has remained unexplained. More and more researchers have inclined to behaviorism and suggested psychological effects as main causes of January effect in stock returns, (Malkiel, 2003).

1.3 Part of the month effect

Ariel (1987) documented another pattern in stock returns - Part of the month[20] and suggested its dependence of January effect. He used data from 1963 to 1981, divided months into two parts and examined daily returns. He observed significantly higher returns during the first half of the month, particularly during first nine days and the last day of the month. The returns were almost 100% higher on these days than the monthly average returns. In contrast, the returns during the second half of the

[20] Part of the month effect is sometimes called Turn of the month or Day of the month effect

month were negative or zero. Ariel (1987) tested the hypothesis of equal returns for the first and the second half of the month. Nonetheless, the hypothesis was rejected on all usually used levels of significance.

Ariel (1987) suggested some explanations but neither of them explained properly the causes of the Part of the month effect. He documented that pre-test bias could influence daily returns during months, which was the problem of data mining. If we first check data and then find a pattern in returns we cannot further test the hypothesis against the same data. However, Ariel (1987) was not the first researcher, who observed the Day of the month pattern in stock returns. Merill (1966), Fosback (1976), and Hirsch (1979) advised to buy stocks before the start of a month and sell them in the second half of the month. Thus, pretest bias could not be considered and hence, the explanation was insignificant. Also neither the explanation of biased data nor a mismatch between trading and calendar time clarified the causes of Part of the month effect. Many hopes were pinned on the explanation using dividend effect, but even dividends were not able to reveal the causes of Day of the month pattern. Finally Ariel (1987) noted that returns of small firms exceeded returns of large firms during both halves of months but the difference was subtle.

Lakonishok and Schmidt (1988) examined the issue in more details for ninety-year period. They found exceptionally high returns at turn of the month, particularly for the last day of the previous month and for the first three days of the current month which confirmed Ariel's (1987) work. The results showed that cumulative rate of return for the four-day period at turn of the month is 0.473 percent against 0.0612 percent for average four day period. The difference was statistically significant.

Ogden (1990) tried to clarify the causes of this anomaly. He illustrated that investors received salaries, dividends, and interests at turn of the month. More money was available and stock demand was increased. However, using data for 1969 - 1986 he was not able to prove this evidence.

Nikkinen, Sahlström, and Äijö (2007) used data from January 1995 to December 2003. They observed that first 3 days in the month were characterized by the highest returns and other days at turn of the month produced positive returns. Hence, they believed that announcements of macroeconomic news played a key role. Nikkinen, Sahlström, and Äijö (2007) estimated the data by GARCH model and concluded that the clustering of macroeconomic news announcements could partially explain the Part of the month effect.

1.4 Other anomalies in stock returns

There are several other anomalies, which caught some attention. Holiday effect is an analogy to Day of the week effect. Merrill (1966) observed high returns on the last day before holidays. Lakonishok and Schmidt (1988) used ninety-year perspective to show that returns on the last day before holidays were 23 times higher than during average day of the year. On the contrary, post-holiday rate of return was negative, but not significantly different from zero. Lastly, Vergin and McGinnis (1999) demonstrated that Holiday effect (for period from 1987 - 1996) almost disappeared for large firms and was substantially lower for small firms.

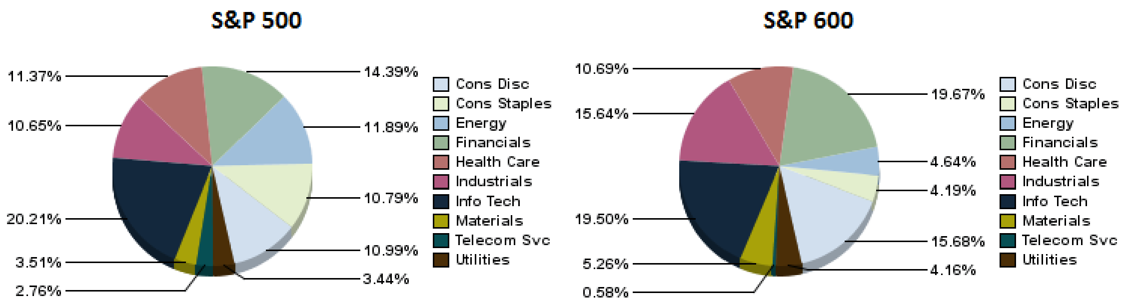
Other patterns such as Turn of the quarter effect or Years ending with 5 effect could also be found but they should not be classified as anomalies. They are rather a result of data mining.

In the following chapters we use data for U.S. stock market and try to examine stock yield anomalies after year 1995.

2 Data

We used one of the main stock indices in the United States - S&P 500 and another popular index - S&P 600 for the sample period[21] from August 18, 1995 to February 28, 2012. Use of these two indices is not a coincidence. S&P 500 is considered the best single gauge of U.S. equity market for companies with large market capitalization which must exceed a \$5 billion limit. S&P 600 is its equivalent for firms with, lower market capitalization under \$300 million. Using these indices we can easily test the phenomenon of higher returns of low capitalized companies in comparison with firms with high capitalization. While S&P 500 covers more than 75% of U.S. equity market, S&P 600 accounts for only 3%. The sector breakdown of both indices is very similar to Figure 1.

Figure 1: S&P breakdown



Source: www.standardpoors.com

The most important element of the sector breakdown is the Information Technology sector which constitutes 20% of U.S. equity and consists of the highest capitalized firm nowadays - Apple Inc. Among other biggest constituents of this sector belong Exxon Mobil Corp, Microsoft Corp, Chevron Corp, AT&T Inc or Procter & Gamble. Industrial, Financial or Consumer Staple companies play a more important role for low capitalization index S&P 600, but the share of these sectors on market equity exceed in both indices a 10% boundary. Adjusted market capitalization of S&P 600 index by price returns is $\$12,418,844.35$ million in comparison with $\$497,049.07$ million of S&P 500 index. One curiosity from stock market is that Ap-

[21]Source: http://finance.yahoo.com/

ple Inc. has larger market capitalization than the whole S&P 600 index consisting of 600 companies.

There are 4163 observations for returns of S&P 500 index and 4161 for returns of S&P 600 index. The difference is caused by two days February 1, 2002 and June 14, 2002 when prices for S&P 600 were not recorded. Stock returns are computed as the log of the first difference of the closing stock prices, which are adjusted for dividends and splits, i.e.:

$$r_t = \log\left(\frac{P_t}{P_{t-1}}\right), \tag{1}$$

where r_t is rate of return for day t, P_t is price of an asset for day t and P_{t-1} is price of an asset for day $t-1$.

We used Dow Jones U.S. Indexes: Industry Indexes for our sector analysis of anomalies in stock returns. Dow Jones U.S. Indexes consist of 10 main indices of broad industries which are classified into 19 Supersectors, 41 Sectors, and 114 Subsectors. All the indices together constitute more than 95% of the market capitalization of all firms in the United States and were first captured on the 14^{th} of February, 2000. We used 6 indices out of the total number of 10 indices. It is naturally possible to use other sector indices such as NASDAQ or NYSE indices, but neither of them have the same desirable properties such as the same period length or are not as properly recorded as abovementioned Dow Jones U.S. Indexes. Table 1 captures 6 selected indices with their general properties[22].

As illustrated in the Table 1 all selected indices together consist of 883 firms and constitute almost 70% of sector allocation which represents more than 66% of the market share. The number of observations is similar, around 2991 of observations. In the following paragraphs, we will look more deeply at industry indices and find the basic characteristics, such as index market capitalization or biggest companies.

Dow Jones U.S. Financials Index covers following sectors: Oil & Gas Producers; Oil Equipment, Services & Distribution; Alternative Energy. Market capitalization of this index amount to 2410.2 billion dollars and among the biggest

[22]Source: www.djindexes.com

Table 1: General properties of sector indices

Index Name	Number of Observations	Number of Components	Sector Allocation
Financials	2990	256	15.47%
Health Care	2990	119	10.64%
Industrials	2991	242	12.61%
Oil & Gas	2991	90	11.32%
Technology	2993	157	17.21%
Telecommunications	2990	19	2.66%

players fall JPMorgan Chase & Co.; Bank of America Corp.; Wells Fargo & Co. or Goldman Sachs Group Inc.

Dow Jones U.S. Health Care Index consists of two sectors: Health Care Equipment & Services and Pharmaceuticals & Biotechnology. These two sectors have market capitalization exceeding 1565.3 billion dollars and biggest components are Johnson & Johnson; Pfizer Inc. or Abbott Laboratories.

Dow Jones U.S. Industrials Index covers following sectors: Construction & Materials; Aerospace & Defense; General Industrials; Electronic & Electrical Equipment; Industrial Engineering; Industrial Transportation; Support Services. Market capitalization of this index amounts to 1909.7 billion dollars. It is mainly influenced by General Electric Co., the weight of which is 11.39% of the index. Other smaller players are Caterpillar Inc. or 3M Co.

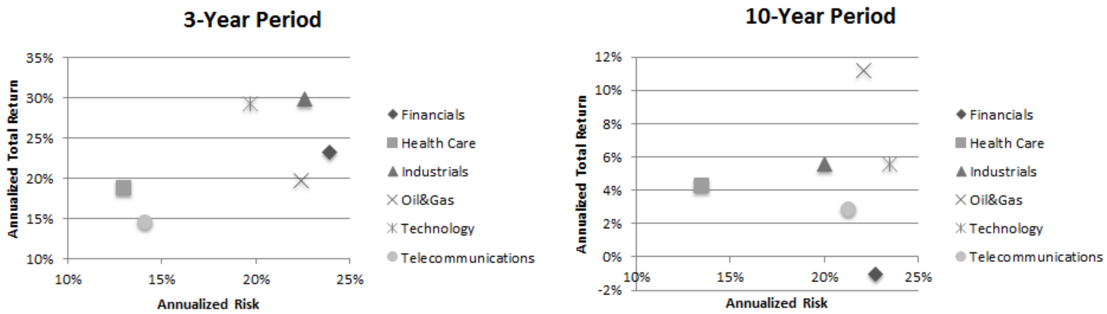
Dow Jones U.S. Oil & Gas Index consists of three sectors: Oil & Gas Producers; Oil Equipment, Services & Distribution; Alternative Energy. The market capitalization of this index is 1672.0 billion dollars. Regarding the issue of the biggest players, the Oil & Gas Index is similar to the Health Care Index. The adjusted weight of Exxon Mobil Corp. is more than 25.41%; the second largest company is Chevron Corp., which has an adjusted weight exceeding 13%. Other companies in this sector are almost irrelevant.

Dow Jones U.S. Technology Index consists of two sectors: Software & Computer Services and Technology Hardware & Equipment. This sector has the highest market capitalization from all sectors exceeding 2585 billion dollars and include the firm with highest market capitalization; Apple Inc., with market capitalization \$506.69 billion. The weight of Apple Inc. takes up more than 22% of the index. Microsoft Corp (9.31%), International Business Machines Corp.(8.87%), or Google Inc. Cl A (6.39%) belong to other big companies in the sector.

Dow Jones U.S. Telecommunications Index includes following two sectors: Fixed Line Telecommunications and Mobile Telecommunications. Market capitalization of this index is much lower than that of previous sectors, specifically 390.9 billion dollars. Almost a half of the market capitalization of this index is constituted by AT&T Inc, specifically 47.88%. The second biggest player in this sector is Verizon Communications Inc. with almost 28% market capitalization.

As we can see in Figure 2, the annualized total return increased significantly in the last 3 years in comparison to the last 10 yeas. This is especially caused by the economic crisis in 2008 and a big drop of asset prices in the same year. Annualized risk[23] remains the same with values around $10 - 25\%$.

Figure 2: Annualized total return / annualized risk



Source: www.djindexes.com

In long-term statistical point of view, it is good to invest into the Health Care sector, which is the least risky or into the Oil & Gas sector, which is the most profitable. The winners remain the same, even if we look at the sector indices, after

[23] Annualized risk is computed se annualized standard deviation: $\delta \cdot \sqrt{N}$, where δ is standard deviation of daily means for last 3 (10) years and N is a number of trading days for last 3 (10) years.

the inception date[24] of December 31, 1991. Since this date Oil & Gas sector achieved the highest cumulative return from all other sectors of 887.29%. The least profitable sector is Telecommunications with 167.61% cumulative return.

[24] For the period prior to its initial calculation on 14^{th} of February, 2000, any such information was back-tested. Source: www.djindexes.com

3 Methodology

There exist several models for testing conditional heteroskedasticity. Engle (1982) was the first one to develope a model known as ARCH. Assuming that mean equation is specified as basic AR(1) model

$$r_t = \alpha_0 + \alpha_1 \cdot r_{t-1} + \epsilon_t, \tag{2}$$

conditional variance, h_t, depends in ARCH model only on the past squared residuals of basic AR(1) model, equation (2):

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \cdot \epsilon_{t-i}^2 \tag{3}$$

Later, Bollerslev (1986) extended this model and let the conditional heteroskedasticity be dependent not only on squared residuals but also on lagged values of h_t:

$$h_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \cdot \epsilon_{t-i}^2 + \sum_{j=1}^{q} \alpha_j \cdot h_{t-j}^2 \tag{4}$$

GARCH models are widely used in financial series because they are able to capture volatility dynamics of data.

To test the stock yield anomalies we chose GARCH(1,1) model with Student-t distribution of errors. We base this model on past empirical results of other researchers such as Berument and Kiymaz(2001); Choudry (2001) or stylized facts and statistical issues of Cont(2001). GARCH(1,1) with Student-t distribution should correct, at least partially, stock returns for volatility clustering[25], leptokurtosis and count on non-normal error distribution containing heavy tails, (Cont, 2001). Yet, there exist other properties of asset returns, which are hard to be captured. Student-t distribution is not the best describing distribution either, because of exponentially truncated stable distribution could better describe the asset returns, (Cont, 2001). However, it is out of scope of this text to examine all statistical issues of asset returns.

For testing of all three major anomalies we used the GARCH(1,1) model with Student-t distribution supplemented by relevant dummy variables. We started with

[25]Volatility clustering = amplitude of the returns varies over time; Engle(2001)

AR(1) model:

$$r_t = \alpha_0 + \alpha_1 \cdot r_{t-1} + \epsilon_t, \tag{5}$$

where r_t is a rate of return for each particular day, r_{t-1} is rate of return for previous day, and ϵ_t is an error term. For the same reason as Berument and Kiymaz (2001), we included lagged rate of return in order to prevent the possibility of having autocorrelated errors. The error term ϵ_t is uncorrelated and has Student-t distribution with zero mean, but time varying variance and n degrees of freedom:

$$\epsilon_t \sim t(0, \sigma_t^2, n) \tag{6}$$

We can break down the variance σ_t^2 into two pieces - ν, which is a stochastic part, and h_t, which is a time dependent standard deviation:

$$\delta_t = \nu \cdot h_t \tag{7}$$

assuming that:

$$\nu \sim N(0, 1) \tag{8}$$

As demonstrated by Bollerslev (1987) Student-t distribution could be more appropriate, when the series have a substantial kurtosis, which is mostly observed in stock return series. We have to use the time varying variance to control for conditional heteroskedasticity, otherwise the the coefficients would not be efficient.

A lot of models allowing for conditional variance have been proposed, but as noted by Bollerslev (2001) GARCH(1,1) is sufficient for most financial series. Putting all the above assumptions together, we can write the last part of our model:

$$h_t^2 = \beta_0 + \beta_1 \cdot h_{t-1}^2 + \gamma_1 \cdot \epsilon_{t-1}^2. \tag{9}$$

Assuming that

$$r_t|\Omega_t \sim f(u_t, h_t, d) \tag{10}$$

is a conditional density function of series r_t, where Ω_t is a given information set containing all information at time t, and d is the number of degrees of freedom, GARCH(1,1) can be estimated using maximum likelihood function suggested by Berndt et al. (1974) and Booth, Hatem, Virtanen and Yli-Olli (1992) as follows:

$$L(\Theta|p,q,m) = \sum_{t=\tau}^{T} logf(u_t, h_t, d). \tag{11}$$

The likelihood function is maximized for all combinations of values of p, q, m which are initially prespecified, $\Theta = \alpha_0, \alpha_1, \beta_0, \beta_1$ and $\tau = max(p, q, m)$.

As suggested by past studies we included some exogenous variables such as day of the week or month variable into the equations (5) and (9), which resulted in allowing the change of stock returns volatility through the change of the intercept of conditional variance.

We used the following models for testing anomalies:

- **Day of the week effect**

$$r_t = \theta_1 \cdot D_1 + \theta_2 \cdot D_2 + \theta_3 \cdot D_3 + \theta_4 \cdot D_4 + \theta_5 \cdot D_5 + \alpha_1 \cdot r_{t-1} + \epsilon_t \tag{12}$$

where $D_1 \ldots D_5$ are dummy variables for each day of the week, which assume 1 for particular day and zero otherwise. The equation of conditional variance for the Day of the week effect is as follows:

$$h_t^2 = \sum_{i=1}^{5} \rho_i \cdot D_i + \beta_1 \cdot h_{t-1}^2 + \gamma_1 \cdot \epsilon_{t-1}^2 \tag{13}$$

- **January effect**

$$r_t = \sum_{i=1}^{12} \varrho_i \cdot M_i + \alpha_1 \cdot r_{t-1} + \epsilon_t \tag{14}$$

where $M_1 \ldots M_{12}$ are dummy variables for each month, which assume 1 for particular month and zero otherwise. The equation of conditional variance for January effect is as follows:

$$h_t^2 = \sum_{i=1}^{12} \lambda_i \cdot M_i + \beta_1 \cdot h_{t-1}^2 + \gamma_1 \cdot \epsilon_{t-1}^2 \tag{15}$$

- **Part of the month effect**

$$r_t = \sum_{i=1}^{5} \upsilon_i \cdot P_i + \alpha_1 \cdot r_{t-1} + \epsilon_t \tag{16}$$

where $P_1 \ldots P_5$ are dummy variables for each part of the month and:

$D_1 = 1$ for first six days in the month and zero otherwise

$D_2 = 2$ for second six days in the month and zero otherwise

$D_3 = 3$ for 13. - 16.(17. ,18. ,19.) days in the month and zero otherwise

$D_4 = 4$ for last but one six days in the month and zero otherwise

$D_5 = 5$ for last six days in the month and zero otherwise

The equation of conditional variance for Part of the month effect is as follows:

$$h_t^2 = \sum_{i=1}^{5} \psi_i \cdot P_i + \beta_1 \cdot h_{t-1}^2 + \gamma_1 \cdot \epsilon_{t-1}^2 \quad (17)$$

Later in the text we will find out that calculation using these models is impossible. Therefore, we have to deal with it using an alternative method. First, we account for heteroskedasticity. We estimate basic AR(1) model along with GARCH(1,1) - equation (5) and (9) respectively. Then, we will get standard errors of the residuals σ_t and standardize the returns:

$$sr_t = \frac{r_t}{\sigma_t} \quad (18)$$

Finally, we will calculate AR(1) model supplemented by dummy variables as (12), (14), (16), using standardized returns, sr_t.

4 Empirical results

This section is divided into five main parts. Initially, we describe basic characteristics of analyzed series. Next, we will focus more on empirical results of the models and try to find seasonal patterns in stock returns. Finally, we will discuss the outcomes of the models with respect to past projects.

4.1 Basic characteristics

Table 2 shows the basic characteristics of the indices such as mean, variance, skewness and kurtosis. It is well illustrated that firms with lower market capitalization generate on average 51% higher profits than firms with higher market capitalization. Higher volatility is associated with higher risk in financial data and firms with lower market capitalization have 27% higher variance than firms with higher market capitalization. Thus, one negative aspect of investing in small firms comes forward. In spite of this, if we compare standardized returns[26] we find out that investing in firms with lower market capitalization is 34% more profitable. Since both indices exhibit excess kurtosis, their distributions are more peaked and have fat tails.

Table 2: Basic statistics

	S&P 500	S&P 600
Ticker	GSPC	SML
Mean	0.0000935	0.000142
Variance	0.0000319	0.0000408
Standardized returns	0.016554	0.022230
Skewness	-0.2245813	-0.2906587
Kurtosis	10.28739	7.772198

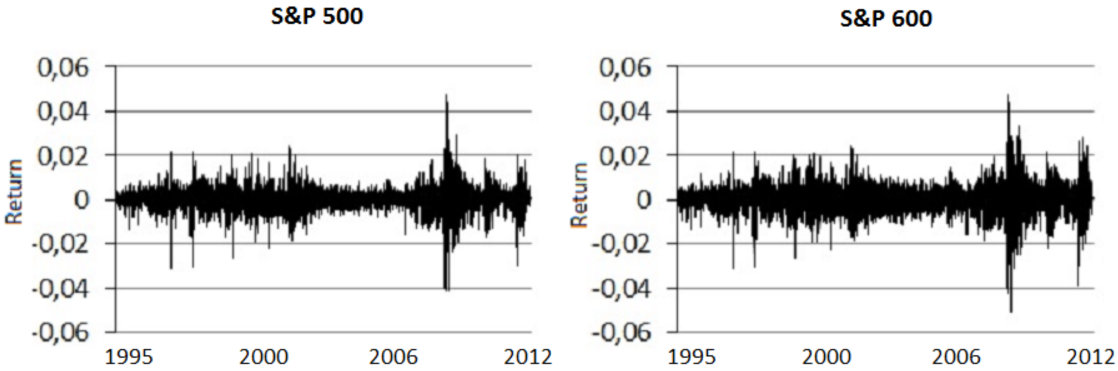
As indicated by Fama (1965) and supported by Choudhry (2001), the distribution of asset returns tends to show excess kurtosis. Excess kurtosis was found in our data, which supports an appropriateness of the usage of the Student-t distribution.

Volatility clustering is another problem we have to face in financial data. As

[26] Computed as $\frac{\mu}{\sqrt{\delta^2}}$, where μ is mean and δ^2 is variance of the series

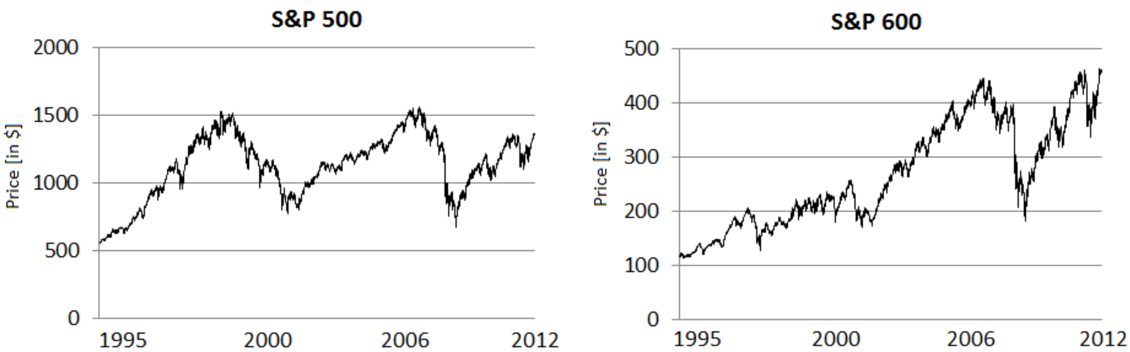
illustrated in Figure 3, volatility clustering was also present in S&P 500 and S&P 600 indices. We computed squared returns and then, we used Box-Pierce Q statistic to test the null hypothesis that all correlations of up to 10 lags are equal to 0, (Lobato, Nankervis and Savin, 2001). The hypothesis was rejected on all usually used levels of significance which indicate a presence of volatility clustering in data.

Figure 3: S&P 500 and S&P 600 returns



It is clearly seen in Figure 4 that the internet bubble in 2000 affected prices only S&P 500 index. Prices of S&P 600 remained. Volatility clustering did not appear in these indices at turn of the century. S&P 500 experienced the biggest appreciation from 1996 to 2000 and despite some drop-downs, it has remained stable ever since.

Figure 4: Index prices



On the contrary, S&P 600 has been steadily increasing except for the crisis outbreak in 2008. As already mentioned, both indices suffered from the crisis in 2008 and stock indices prices tumbled by almost 50%. However, S&P 600 has already emerged from the crisis and reached even higher value than in 2007. S&P

500 has also recovered.

Table[27] 3 shows the basic statistics such as mean, variance, standardized returns, and kurtosis for all sector indices. As we can see in the table the range of mean returns is approximately around zero[28]. The mean returns are similar to main S&P 500 and S&P 600 indices. Nevertheless variance, and thus risk differs. There is no such a rule that a higher risk does necessarily mean higher returns. If we look at the statistics for Oil & Gas and Technology sector and compare them we find an interesting fact. Although the mean returns for Oil & Gas sector are positive, specifically 0.0001651, compared to negative returns of -0.0000725 for Technology sector, Oil & Gas sector has 17.8% lower variance and thus risk.

Table 3: Basic statistics of sector indices

Index Name	Ticker	Mean	Variance	Standardized Returns	Kurtosis
Financials	DJUSFN	-0.0000192	0.0000846	-0.002087	14.23576
Health Care	DJUSHC	0.0000482	0.0000331	0.008377	30.50289
Industrials	DJUSIN	0.0000286	0.0000475	0.004149	7.791883
Oil & Gas	DJUSEN	0.0001651	0.0000669	0.020185	12.33317
Technology	DJUSTC	-0.0000725	0.0000813	-0.00804	7.940238
Telecommunications	DJUSTL	-0.0001327	0.0000528	-0.018262	13.46743

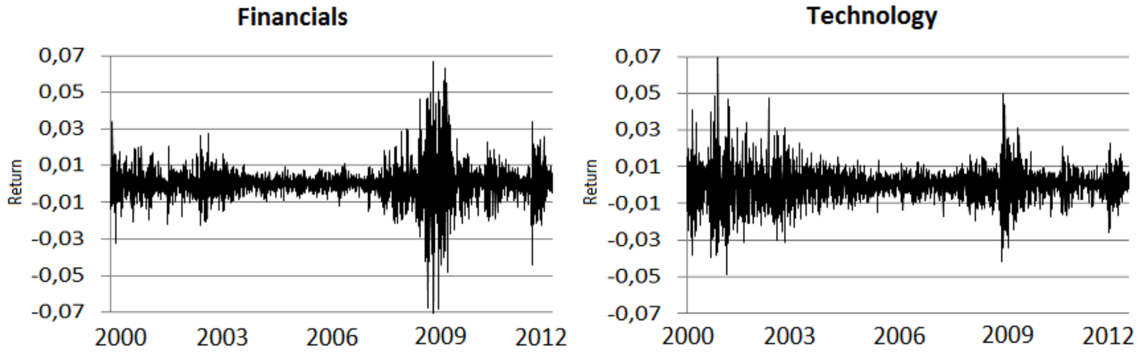
As indicated by Fama (1965) and Choudhry(2001), financial data have substantial kurtosis, which can be partly corrected by Student-t distribution. Keeping in mind that kurtosis of normal distribution is 3, we found similar kurtosis to S&P 500 and S&P 600 in the sector indices as well, ranging from 7.79 to 30.50. The kurtosis value of 30.50 in Health Care sector is a rare example. Kurtosis of all other indices ranged from 7.7 to 14.2.

Volatility clustering in sector indices is not as obvious at the first sight as for S&P 500 and S&P 600, which could be caused by smaller trade volume. All that said, we can see some evidence of volatility clustering in Figure 5. We used returns

[27] Complete table in Appendix.

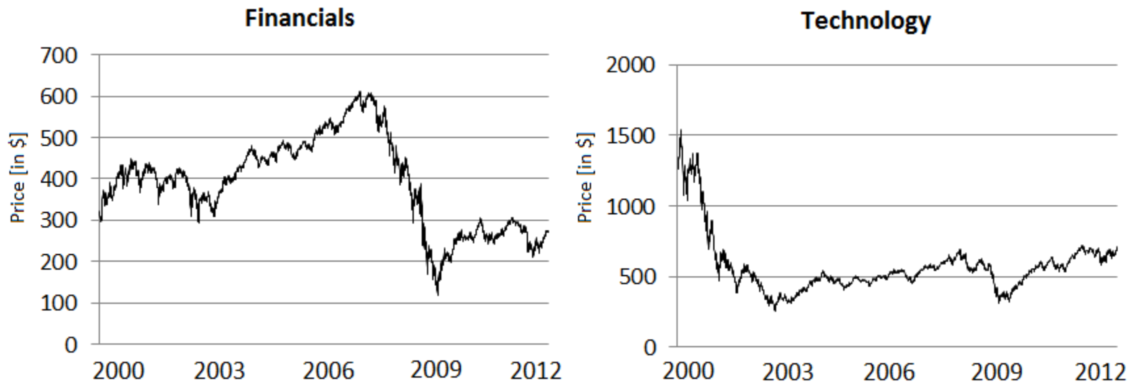
[28] More specifically from -0.0001327 to 0.0001651

Figure 5: Sector returns



of Dow Jones U.S. Financials Index and Dow Jones U.S. Telecommunications Index as a representative sample but behavior of all other sector indices is the same. We computed the squared returns of all sector indices and using the Ljung Box Q statistic we tested the null hypothesis of no autocorrelation of the returns up to 10 lags. The hypothesis was rejected for all lags on all usually used levels of significance which supports the volatility clustering hypothesis.

Figure 6: Sector prices



The internet bubble affected mostly information technology sector and all these companies are covered in Dow Jones U.S. Technology Index. Thus, the consequences of the internet bubble are well demonstrated in Figure 6. Technology sector prices plunged 80% between 2000 and 2003 and volatility clustering increased considerably in that period. On the other hand, financial crisis that started 5 years ago, did not lead to a large price dropdown of stocks of technology companies. Prices have remained stable since 2003. Behavior of Financial sector and all other indices was different. The internet bubble did not affect the indices' prices at all, but the financial crisis did. The Financial index prices dropped by 80% from 610$ to 120$ between 2007 - 2009 and volatility clustering was evident at the time.

In following chapters we will use data for S&P 500, S&P 600, and sector indices and try to find Day of the week, January, and Part of the month effect between the years[29] 1996 - 2012.

4.2 Day of the week effect

In this part we focus on the Day of the week effect and try to find significant patterns in daily returns. Using formulas (12) and (13) we wanted to calculate the results. However, the GARCH model using all the dummy variables was too extensive and the models were not able to converge in any statistical software package. Thus, we were forced to switch to an alternative model (5), (9), and (14). First, we computed standardized residuals ϵ_t/h_t, (5), (9).

Table 4: Ljung Box-Q test

	S&P 500	S&P 600	DJUSEN	DJUSFN	DJUSHC	DJUSIN	DJUSTC	DJUSTL
AC 1	0.0072	0.0071	0.0165	0.02	0.0015	-0.0069	-0.0005	-0.0045
Q(1)	0.21489	0.21132	0.81485	1.21	0.00677	0.14308	0.00069	0.06012
Prob > Q	0.643	0.6457	0.3667	0.2749	0.9344	0.7052	0.9791	0.8063
AC 2	-0.0164	-0.01	-0.0284	-0.0132	-0.0593	-0.0236	-0.0122	-0.0102
Q(2)	1.05	0.62389	3.225	1.89	10.521	1.71	0.44642	0.3693
Prob > Q	0.5141	0.732	0.1994	0.4255	0.0052*	0.4051	0.7999	0.8314
AC 3	-0.0223	0.0184	-0.0135	-0.0202	-0.0062	0.0035	-0.0128	-0.0121
Q(3)	3.51	2.0403	3.22	2.94	10.635	1.47	0.93553	0.80638
Prob > Q	0.3333	0.5641	0.2871	0.4042	0.0139	0.6053	0.8168	0.8479
AC 5	-0.0366	-0.0227	-0.0204	-0.0417	-0.026	-0.0291	-0.0188	-0.0073
Q(5)	8.99	4.59	5.0463	8.88	12.688	6.31	2.61	0.9034
Prob > Q	0.1095	0.4477	0.4103	0.1395	0.0265	0.2851	0.7574	0.9034
AC 10	0.0276	-0.0037	0.0164	0.0026	-0.0077	-0.0054	-0.0029	-0.0068
Q(10)	14.245	10.482	5.97	10.554	14.654	12.077	5.89	3.886
Prob > Q	0.1621	0.3993	0.8178	0.3933	0.1452	0.2799	0.8302	0.9523

H_0: no autocorrelation in standardized residuals

H_A: standardized residuals are correlated

* We reject the null hypothesis on 10 percent level of significance

[29] For sector indices we used period from 2000 to 2012

Then, in order to validate the model we employed Ljung Box-Q test to check for serial correlation, (Choudry, 2001). As we can see in Table 4 we could not reject the hypothesis of no autocorrelation in the stock returns. This suggested that there was no need for a higher order GARCH model. Then, satisfying non-explosiveness (19) and non-negativity (20) of conditional variance (9), we finally validated the model.

$$\beta_0 + \beta_1 < 1 \tag{19}$$

$$\gamma_1, \beta_0, \beta_1 > 0 \tag{20}$$

Table 5: Daily statistics summary

		Monday	Tuesday	Wednesday	Thursday	Friday	Lagged returns
S&P 500	Coef.	0.0256	0.0272	0.0452	0.0137	-0.0121	-0.0248
	Std. Dev.	(0.0355)	(0.03283)	(0.0361)	(0.0340)	(0.0358)	(0.0170)
	P value	[0.471]	[0.407]	[0.211]	[0.685]	[0.734]	[0.146]
S&P 600	Coef.	-0.0316	0.0372	0.0750	0.0351	0.0318	0.0363
	Std. Dev.	(0.0344)	(0.03371)	(0.03585)	(0.0340)	(0.03665)	(0.0165)
	P value	[0.359]	[0.269]	[0.036]	[0.301]	[0.385]	[0.028]**
DJUSEN	Coef.	0.02894	0.0394	0.0475	0.0118	0.0395	-0.0078
	Std. Dev.	(0.04209)	(0.0398)	(0.0385)	(0.0400)	(0.0461)	(0.0189)
	P value	[0.492]	[0.322]	[0.217]	[0.768]	[0.392]	[0.68]
DJUSFN	Coef.	0.0169	0.0276	0.03234	-0.0125	-0.0625	-0.0407
	Std. Dev.	(0.0409)	(0.0387)	(0.0415)	(0.03999)	(0.0449)	(0.0195)
	P value	[0.678]	[0.476]	[0.436]	[0.753]	[0.164]	[0.037]**
DJUSHC	Coef.	0.0278	0.0420	0.0459	-0.0001	-0.1025	-0.0313
	Std. Dev.	(0.0430)	(0.0417)	(0.0426)	(0.0414)	(0.0466)	(0.0169)
	P value	[0.517]	[0.313]	[0.282]	[0.997]	[0.028]*	[0.064]*
DJUSIN	Coef.	0.0080	0.0189	0.0154	0.0301	-0.0396	-0.0270
	Std. Dev.	(0.0424)	(0.0406)	(0.0411)	(0.0397)	(0.0432)	(0.0176)
	P value	[0.85]	[0.641]	[0.707]	[0.448]	[0.359]	[0.125]
DJUSTC	Coef.	0.0184	0.0082	0.0588	0.0476	-0.1038	-0.0147
	Std. Dev.	(0.0437)	(0.0397)	(0.0398)	(0.0395)	(0.0420)	(0.0201)
	P value	[0.673]	[0.835]	[0.139]	[0.228]	[0.013]**	[0.463]
DJUSTL	Coef.	0.0194	-0.0033	-0.0254	-0.0189	-0.0636	-0.0093
	Std. Dev.	(0.0431)	(0.0411)	(0.0428)	(0.0434)	(0.0051	(0.0142)
	P value	[0.653]	[0.935]	[0.553]	[0.663]	[0.209]	[0.513]

"Coef." denotes average daily return in each day of the week, "Std. Dev." means standard deviation, "P value" denotes p-value for each coefficient and tests the null hypothesis that average daily return is equal to zero.

** We reject the null hypothesis on 5 percent level of significance
* We reject the null hypothesis on 10 percent level of significance

Lowest returns for each index are coloured red.
Highest returns for each index are coloured green.

Figure 5 shows the basic characteristics such as mean, standard deviation, and p-value of each t-statistic for all weekdays and for all indices after adjusting for the first order autocorrelation. We can clearly see that most coefficients for particular days were not significant and same stands for lagged returns. This suggests that yesterday's returns do no influence today's returns. However, this was not our objective. Daily returns were on average positive in most days, with the exception for Friday. Dow Jones U.S. Technology Index was the only index which was characterized negative negative returns on Wednesday. On the other hand, except for S&P 600 and Dow Jones U.S. Oil & Gas Index all indices had negative returns on Friday. The highest returns occurred on average on Wednesday, equal to 0.037; the lowest returns were on Friday, -0.039 on average. We did not observe such differences in standard deviation, which ranges between 0.035 and 0.05. Standard deviation was the highest on Friday and the lowest on Tuesday.

Figure 7: Daily returns

Figure 7 demonstrates the fact that returns systematically increased till Wednesday then started to decrease with negative returns on Friday. Dow Jones U.S. Oil & Gas Index was the only index, which produced positive returns on all days and Dow Jones U.S. Telecommunications Index was the only index, which had negative returns on average. All sector indices except for the above-mentioned Dow Jones U.S. Oil & Gas Index were less profitable than main indices S&P 500 and S&P 600. S&P 600 had 49% higher returns than S&P 500 with the same standard deviation 0.034.

We employed Wald-chi squared statistic to test the null hypothesis that all coefficients were jointly equal to zero or equal to each other. As illustrated in Figure 6 we could not reject the hypothesis that all coefficients were equal to zero, except for Dow Jones U.S. Technology Index. When we excluded the variable for Wednesday, which in most cases had the highest returns of the week, we tested the same hypothesis and the results confirmed the previous findings. Subsequently, we tested the joint equality of all parameters and the observed results suggested that we could not reject the hypothesis that all parameters are equal to each other. When we excluded coefficient for Wednesday we confirmed our findings as well.

Table 6: Wald-chi squared test

	S&P 500	S&P 600	DJUSEN	DJUSFN	DJUSHC	DJUSIN	DJUSTC	DJUSTL
$chi2_1$	3.09	8.04	3.79	3.38	7.68	1.81	9.98	2.35
Prob > chi2	0.6865	0.1538	0.5797	0.6413	0.1745	0.8754	0.0759*	0.7984
$chi2_2$	1.46	3.99	2.29	2.75	6.37	1.65	7.73	2.00
Prob > chi2	0.8329	0.4067	0.6833	0.5999	0.1735	0.8003	0.1020	0.7362
$chi2_3$	1.42	4.93	1.40	3.36	7.51	1.63	9.78	1.71
Prob > chi2	0.8411	0.2942	0.8437	0.5001	0.1113	0.8030	0.0443**	0.7862
$chi2_4$	0.81	2.95	1.09	2.70	6.35	1.58	7.64	1.65
Prob > chi2	0.8462	0.3993	0.7801	0.4408	0.0958*	0.6647	0.0540*	0.6490

$chi2_1$: all coefficients (Monday .. Friday) are jointly equal to zero
$chi2_2$: Monday, Tuesday, Thursday, Friday are jointly equal to zero
$chi2_3$: all coefficients (Monday .. Friday) are jointly equal
$chi2_4$: Monday, Tuesday, Thursday, Friday are jointly equal to zero

** We reject the null hypothesis on 5 percent level of significance
* We reject the null hypothesis on 10 percent level of significance

For the sake of completeness and additional validation of GARCH model, we estimated mean equation (12) using OLS, (Berument and Kiymaz, 2001). We observed interested results, Table[30] A-2. While GARCH model showed the highest returns on Wednesday and lowest returns on Friday, we observed different results using OLS. The highest returns occurred on Tuesday and the lowest not only on Friday but also in other days of the week. Wednesday was the only day of the week when returns were positive for all indices. We performed Langrange multiplier test for presence of conditional heteroskedasticity our in data, (Furno, 2000). The hypothesis was rejected on all usually used levels of significance. Hence, the result validated the usage of GARCH(1,1) model. The results indicates that using GARCH model and

[30]Found in Appendix

allowing for conditional heteroskedasticity was very important.

As illustrated in this section, after controlling for conditional heteroskedasticity returns are the highest on Wednesday and the lowest on Friday. However, we can conclude that there exists no statistically significant Day of the week effect in returns as demonstrated by Wald-chi squared test, Figure 6.

4.3 January effect

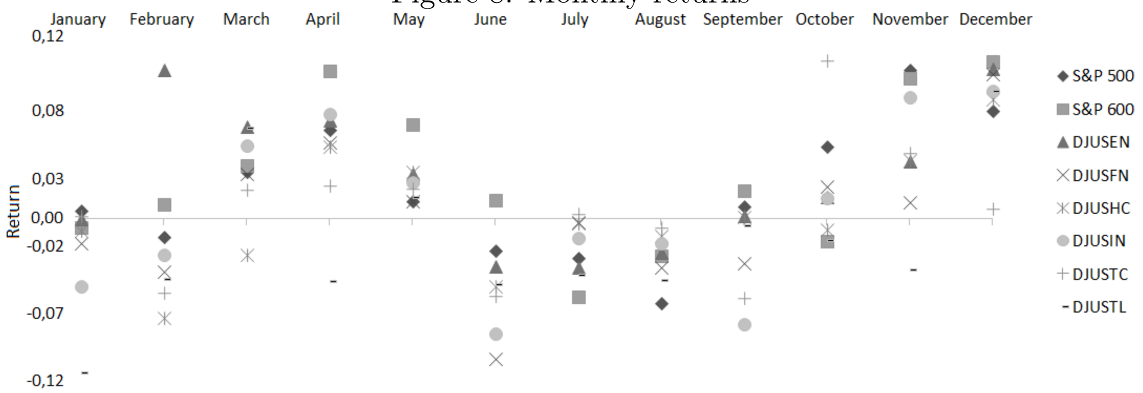
In this part we focus on January effect. We have already validated our GARCH model in the previous part.

Table 7: Monthly statistics summary

	S&P 500	S&P 600	DJUSEN	DJUSFN	DJUSHC	DJUSIN	DJUSTC	DJUSTL
January	0.0056	-0.0069	-0.0002	-0.0186	-0.0095	-0.0504	0.0019	-0.1142
	(0.0490)	(0.5569)	(0.0616)	(0.0573)	(0.0646)	(0.0578)	(0.0578)	(0.0605)
February	-0.0140	0.0103	0.1098	-0.0392	-0.0735	-0.0269	-0.0547	-0.0447
	(0.0539)	(0.0576)	(0.0693)	(0.0629)	(0.0636)	(0.0626)	(0.0670)	(0.0682)
March	0.0346	0.0387	0.0675	0.0327	-0.0268	0.0535	0.0214	0.0673
	(0.0507)	(0.0546)	(0.0598)	(0.0590)	(0.0671)	(0.0607)	(0.0609)	(0.0688)
April	0.0653	0.1092	0.0727	0.0560	0.0528	0.0768	0.0245	-0.0463
	(0.0537)	(0.0562)	(0.0662)	(0.0627)	(0.0688)	(0.0615)	(0.0616)	(0.0669)
May	0.0124	0.0696	0.0327	0.0128	0.0340	0.0266	0.0222	0.0158
	(0.0545)	(0.0572)	(0.0620)	(0.0647)	(0.0664)	(0.0639)	(0.0626)	(0.0686)
June	-0.0241	0.0132	-0.0359	-0.1039	-0.0507	-0.0859	-0.0573	-0.0486
	(0.0537)	(0.0569)	(0.0629)	(0.0604)	(0.0599)	(0.0629)	(0.0649)	(0.0710)
July	-0.0296	-0.0584	-0.0368	-0.0028	-0.0034	-0.0149	0.0034	-0.0417
	(0.0499)	(0.0533)	(0.0585)	(0.0579)	(0.0624)	(0.0581)	(0.0593)	(0.0615)
August	-0.0633	-0.0275	-0.0257	-0.0367	-0.0134	-0.0183	-0.0067	-0.0458
	(0.0509)	(0.0558)	(0.0610)	(0.0600)	(0.0639)	(0.0620)	(0.0623)	(0.0694)
September	0.0083	0.0200	0.0013	-0.0335	0.0006	-0.0786	-0.0592	-0.0051
	(0.0510)	(0.0541)	(0.0599)	(0.0550)	(0.0625)	(0.0586)	(0.0603)	(0.0630)
October	0.0526	-0.0169	0.0157	0.0231	-0.0081	0.0149	0.1167	-0.0161
	(0.0475)	(0.0496)	(0.0569)	(0.0593)	(0.0614)	(0.0603)	(0.0580)	(0.0656)
November	0.1098	0.1034	0.0419	0.0118	0.0430	0.0899	0.0483	-0.0383
	(0.0560)	(0.589)	(0.0648)	(0.0625)	(0.0625)	(0.0659)	(0.0644)	(0.0673)
December	0.0794	0.1163	0.1104	0.1064	0.0884	0.0943	0.0070	0.0940
	(0.0590)	(0.0576)	(0.0764)	(0.0753)	(0.0757)	(0.0753)	(0.0742)	(0.0792)
Values in first rows represent average daily returns in each day of the week, values in parenthesis represent standard deviation.								
Lowest returns for each index are coloured red. Highest returns for each index are coloured green.								

Figure 7 shows the basic characteristics, such as mean and standard deviation. Just as in Day of the week effect model, majority of monthly dummy variables and lagged returns were insignificant. The mean returns for each month were very volatile, which is well illustrated in Figure 8. A period with higher returns was replaced by a period with lower returns and vice versa. A beginning of a year yielded negative returns. Higher returns accumulated in spring months, such as March, April, and May. This period was substituted by period with negative returns for all summer months, particularly the lowest returns of -0.049 occurred in June. Finally, the end of the year was characterized by extraordinarily high returns with the highest returns in December, equaling on average to 0.087. Standard deviation ranges from 0.057 to 0.072. Although December had the highest returns, it also had the highest volatility, standard deviation was 0.07162 on average. The lowest standard deviation was in October, 0.05736. Other indices ranged between 0.58 and 0.63. However, controlling for a risk in form of volatility, December was still the most favorable month for investors, followed by March and November. In this respect, June was the worst month for investors.

Figure 8: Monthly returns



S&P 500 index was the only index which had positive returns in January. Dow Jones U.S. Telecommunications Index was characterized by the lowest returns, equaling to -0.1142 in January. On the other hand, Dow Jones U.S. Technology Index was characterized by the highest returns, equaling to 0.1167. However, it is surprising that the highest returns occurred in October.

Employing Wald statistic, we tested the null hypothesis that all coefficients were equal to zero and all coefficients were equal to each other. Both hypotheses could not be rejected on any level of significance. Excluding the coefficient for December improved our findings.

Table 8: Wald-chi squared test

	S&P 500	S&P 600	DJUSEN	DJUSFN	DJUSHC	DJUSIN	DJUSTC	DJUSTL
chi2_1	11.13	14.68	8.74	7.48	5.10	10.67	7.39	8.62
Prob > chi2	0.5179	0.2594	0.7252	0.8246	0.9544	0.5570	0.8310	0.7352
chi2_2	9.32	10.65	6.66	5.50	3.64	9.12	7.38	7.20
Prob > chi2	0.5923	0.4734	0.8258	0.9046	0.9754	0.6108	0.7675	0.7823
chi2_3	9.77	11.71	6.97	7.45	5.10	10.63	7.21	7.19
Prob > chi2	0.5515	0.3858	0.8017	0.7619	0.9261	0.4750	0.7819	0.7839
chi2_4	8.61	9.14	5.62	5.22	3.57	9.11	7.21	4.86
Prob > chi2	0.5697	0.5186	0.8459	0.8758	0.9654	0.5216	0.7056	0.9006

chi2_1: all coefficients (January .. December) are jointly equal to zero
chi2_2: January .. November are jointly equal to zero
chi2_3: all coefficients (January .. December) are jointly equal
chi2_4: January .. November are jointly equal to zero

** We reject the null hypothesis on 5 percent level of significance
* We reject the null hypothesis on 10 percent level of significance

As in the previous section, we used OLS estimation to complete our findings about January effect, Table A-4. The outcomes were different from those using GARCH model. Although the lowest returns occurred in summer months as well, the highest returns were scattered across the whole year. The findings were not only different from GARCH outcomes but also from findings of previous researchers. Then, we performed the Lagrange multiplier test which indicated the presence of conditional heteroskedasticity in our data. This also validated the usage of GARCH model. As demonstrated above, allowing for conditional variance by utilizing GARCH model was necessary.

Allowing for conditional heteroskedasticity we can see that the highest returns concentrate in December and the lowest in summer months. Nevertheless,as demonstrated by Wald test we can conclude there is no monthly pattern in our data.

4.4 Part of the month effect

Part of the month effect is the last calendar anomaly we wanted to find in our data. Figure 9 shows the basic characteristics for part of the month returns. Just as in the previous parts, most of the dummy variables for parts of the month and for lagged

Table 9: Part of the month statistics summary

		Part 1	Part 2	Part 3	Part 4	Part 5	Lagged returns
S&P 500	Coef.	0.1199	-0.0562	0.0766	-0.0469	0.0058	-0.02702
	Std. Dev.	(0.0322)	(0.0350)	(0.0332)	(0.0353)	(0.0345)	(-0.017)
	P value	[0.000]**	[0.108]	[0.021]**	[0.185]	[0.867]	[0.111]
S&P 600	Coef.	0.0775	-0.0604	0.0585	-0.0267	0.1039	0.03215
	Std. Dev.	(0.0342)	(0.0363)	(0.0353)	(0.0374)	(0.0353)	(-0.0166)
	P value	[0.023]**	[0.096]*	[0.098]*	[0.474]	[0.003]*	[0.052]*
DJUSEN	Coef.	0.07039	-0.02129	0.04387	0.00489	0.04673	-0.00782
	Std. Dev.	(-0.0388)	(-0.0416)	(-0.0396)	(-0.0423)	(-0.0424)	(-0.019)
	P value	[0.070]*	[0.609]	[0.268]	[0.908]	[0.271]	[0.681]
DJUSFN	Coef.	0.04913	-0.05148	0.01789	-0.07448	0.06007	-0.04334
	Std. Dev.	(-0.038)	(-0.0407)	(-0.0359)	(-0.0418)	(-0.0428)	(-0.0194)
	P value	[0.197]	[0.207]	[0.618]	[0.075]*	[0.161]	[0.026]**
DJUSHC	Coef.	0.03585	-0.03636	0.07392	-0.07548	0.00998	-0.03315
	Std. Dev.	(-0.0405)	(-0.0432)	(-0.0412)	(-0.0422)	(-0.0431)	(-0.0169)
	P value	[0.377]	[0.400]	[0.073]*	[0.074]*	[0.817]	[0.051]*
DJUSIN	Coef.	0.06269	-0.06404	0.05016	-0.05257	0.03559	-0.02904
	Std. Dev.	(-0.0383)	(-0.0398)	(-0.0389)	(-0.0428)	(-0.0433)	(-0.0177)
	P value	[0.102]	[0.108]	[0.197]	[0.219]	[0.411]	[0.100]*
DJUSTC	Coef.	0.08135	-0.03479	0.03635	-0.03463	-0.01854	-0.01486
	Std. Dev.	(-0.0385)	(-0.0409)	(-0.0385)	(-0.0423)	(-0.0431)	(-0.0201)
	P value	[0.035]**	[0.395]	[0.345]	[0.413]	[0.667]	[0.459]
DJUSTL	Coef.	0.01562	-0.11271	-0.02764	-0.07363	0.10735	-0.01654
	Std. Dev.	(-0.0401)	(-0.0438)	(-0.0439)	(-0.0431)	(-0.0453)	(-0.0144)
	P value	[0.703]	[0.010]**	[0.528]	[0.088]*	[0.018]**	[0.251]

"Coef." denotes average daily return in each day of the week, "Std. Dev." means standard deviation, "P value" denotes p-value for each coefficient and tests the null hypothesis that average daily return is equal to zero.

** We reject the null hypothesis on 5 percent level of significance

* We reject the null hypothesis on 10 percent level of significance

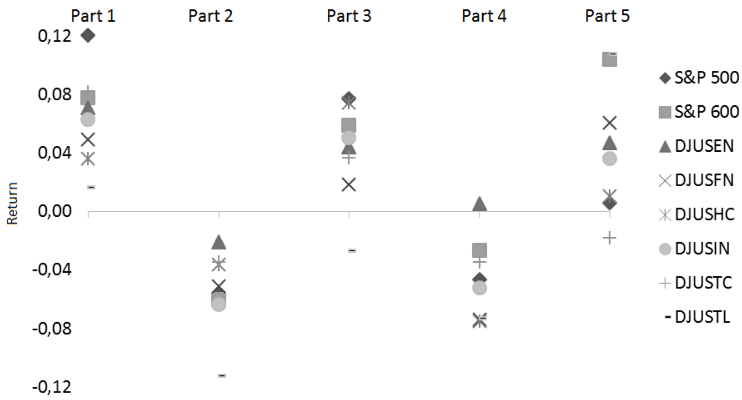
Lowest returns for each index are coloured red.

Highest returns for each index are coloured green.

returns were insignificant. As illustrated in Figure 9 average returns for individual parts of the month were very volatile.

Returns were high in the beginning, middle, and end of the month. On the contrary, the second and the fourth part of the month were characterized by negative returns. Therefore, we could find only two consecutive parts with positive returns: the first and the last part. The highest returns were in the first part, equaling to 0.064, and the lowest returns were in the second part, equaling to -0.054. All indices reported on average positive returns on Monday. On the contrary, all indices had negative returns on Tuesday. Dow Jones U.S. Telecommunications Index is the only index which had on average negative returns. Not surprisingly, Dow Jones U.S. Telecommunications Index was the only index with negative returns in the third part of the month. Standard deviation ranged between 0.037 and 0.041. The highest standard deviation was found on Friday. Interestingly, the beginning of the month not only had the highest returns, but also the lowest standard deviation. Thus, we can conclude that the first 6 days in the month were the most favorable days for investors. On the contrary, second part of the month was the least remunerative.

Figure 9: Part of the month returns



The lowest returns with value of -0.075 belonged to the fourth part of the month and to Dow Jones U.S. Health Care Index. The highest returns, equaling to 0.1199, occurred in the first part of the month and were secured by S&P 500 Index. S&P 600 had 54% higher returns than S&P 500 with similar standard deviation.

Using Wald statistic, we tested the hypothesis that returns in all parts of the month were jointly equal to zero. As shown in Figure 10 this hypothesis was rejected for both main indices S&P 500 and S&P 600 on all usually used levels of significance and for Dow Jones U.S. Telecommunications Index. Then we tested the hypothesis that returns in all parts of the month are equal to each other. This hypothesis was rejected on 10% level of significance for 6 out of 8 indices and for 3 out of 8 indices on 1% level of significance.

Table 10: Wald-chi squared test

	S&P 500	S&P 600	DJUSEN	DJUSFN	DJUSHC	DJUSIN	DJUSTC	DJUSTL
chi2 $_1$	23.46	19.74	5.89	8.67	7.88	9.17	6.94	15.56
Prob > chi2	0.0003**	0.0014**	0.3168	0.1229	0.1628	0.1025	0.2255	0.0082**
chi2 $_2$	21.02	15.75	3.24	8.65	7.86	8.99	6.66	14.58
Prob > chi2	0.0003**	0.0034**	0.5187	0.0704*	0.0968*	0.0615*	0.1548	0.0057**

chi2 $_1$: all coefficients (Part 1 .. Part 5) are jointly equal to zero
chi2 $_2$: all coefficients (Part 1 .. Part 5) are jointly equal

** We reject the null hypothesis on 5 percent level of significance
* We reject the null hypothesis on 10 percent level of significance

In addition to GARCH model we estimated the mean equation also by OLS, Table (A-5). Comparing the results of OLS and GARCH estimation, we can conclude that the findings were similar. Returns were in first, third and fifth part on average positive. On the contrary, in second and fourth part the returns were on average negative. Interestingly, Dow Jones U.S. Telecommunications Index produced not only the highest but also the lowest returns in absolute values. Computing the Langrange multiplier test we found the presence of conditional heteroskedasticity in our data. Thus, we can conclude that the usage of GARCH model was validated.

The Part of the month effect is in contrast to the Day of the week effect or the January effect the only seasonal pattern, which has occured in stock returns recently.

4.5 Discussion

The majority of past projects showed that there were seasonal patterns in stock returns and the highest returns occurred on Friday and the lowest returns on Monday (Keim and Stambaugh, 1983 or Solnik and Bousquet, 1990). As described in section 4.2, we definitely could not have supported the finding of high returns on Friday. Coincidentally, some empirical projects have recently shown that the highest returns on Wednesday are not an exception, (Berument and Kyimaz, 2001). Although we came to the same conclusion, i.e. Wednesday had the highest returns of the week, we could not support the hypothesis of seasonal patterns. We were not able to reject the hypothesis of equal coefficients for each day of the week, which suggests that there was no Day of the week effect for S&P 500, S&P 600 within 1996 - 2012 and for Dow Jones sector indices during 2000 - 2012.

The same applies to the January effect. Although Choudry (2001) and many other authors showed that the highest returns occured in January, we contradict this theory. Data for both main indices between 1996 - 2012 and sector indices between 2000 - 2012 showed that January has negative returns and the highest returns occur in December. Nevertheless, the January effect was not present in the data either, which was proved by Wald test.

The Part of the month effect is the only pattern, which was observed in our data. As demonstrated in Figure 9, beginning of the month was characterized by the highest returns, which supports Ariel's (1987) findings. Although we could not confirm all Ariel's results, e.g. negative returns at the end of the month, we were able to reject the null hypothesis that returns in all parts of the month are equal. Thus, we can conclude that the Part of the month effect was partially present in our data.

We have shown that seasonal patterns hardly emerged in stock returns. However, one thing is evident - allowing for conditional variance, lower capitalized firms make higher returns than firms with higher capitalization. Thus, it is wiser to invest into small companies.

Conclusion

The aim of this bachelor thesis was to verify the efficiency of U.S. stock market, confirm the appearance of calendar stock anomalies, and then try to find the investment strategy. We focused on comparison of low and highly capitalized companies. The uniqueness of this thesis lies in unusual approach to calendar anomalies, specifically in the examination of anomalies across the industrial sectors. Finally, we discussed the results with outcomes of other researchers, refuted the findings of some anomalies, and confirmed the appearance of others.

At first, we have to say we were not able to disprove efficiency of the market based on calendar returns. Days of the week or other calendar parameters do not influence the stock prices at all. However, it is not a straightforward interpretation and doubts about efficiency still exist. Allowing for conditional heteroskedasticity the coefficient for lagged returns is a significant[31] determinant of today's returns for more than 20% of indices. This indicates that yesterdays's returns have some impact on today's returns.

The day of the week was the first examined anomaly. In comparison with past studies we cannot agree that Monday has significantly lower returns and Friday higher returns than other days of the week. On the contrary, *Friday's returns* were the *lowest ones* in most cases. Slightly positive returns on Monday were getting higher until Wednesday and then started to fall. *The highest returns* were achieved *on Wednesday* in 6 out of 8 indices. We tested the null hypothesis of joint equality of all coefficients which could not be rejected on any level of significance. Thus, this indicates that although Wednesday has the highest and Friday the lowest returns, *we did not find any statistically significant daily pattern.*

Next examined anomaly was the January effect. Just as in the previous case the results of our model differed from past findings. January returns were not the highest in the year but fit into the average. Surprisingly, *the highest returns* occurred at the end of the year, mostly *in December*. On the other, hand *summer months* achieved *the lowest returns*. Testing joint hypothesis of equality of all coefficients

[31] On the 5% level of significance

showed that *no Day of the month pattern* appeared recently in stock markets.

The Part of the month effect is partly related to the January effect. We divided each month into five parts and observed the outcomes of the models. Interestingly, positive returns occurred in odd parts, while even parts showed negative returns. *Beginning of the month* produced *the highest returns*. On the contrary, *the second part of the month had the lowest returns*. Unlike the Day of the week or the January effect, the *Part of the month effect* was the only calendar anomaly, which *occurred in stock returns*. Joint equality of the coefficients was rejected on 10% level of significance for 6 out of 8 indices and for some indices, the significance was much stronger.

Regarding the issue of low and highly capitalized companies, *smaller firms generate 51% higher profits*. In spite of the fact that lower capitalized companies have higher risk compared to the standardized returns, we can conclude that investing in lower capitalized companies is on average 35% more remunerative.

Sector indices are in general less profitable and more volatile. *Oil* & *Gas* sector is the only sector which achieved *higher returns* than general S&P 500 and S&P 600 indices. Dow Jones U.S. Telecommunications Index, which is constituted mainly by AT&T Inc. or Verizon Communications Inc., suffered the lowest returns.

As demonstrated above, *we were not able to determine an investment strategy* based on calendar anomalies. The only significant pattern, which occurred in our data and was supported by past studies, is that low capitalized companies earn on average higher profits than highly capitalized companies. However, as suggested by Thaler (1987), small trading volume, large bid-ask spreads, and transactional costs militate against investments into small companies and possible trading strategy.

Anomalies in stock markets remain still an unsolved area. An examination of anomalies in other securities, such as Treasury bills, is an interesting field for further research. Another point of interest could be the examination of anomalies in industrial sectors around the world.

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Appendix

Figure A-1: Sectoral returns

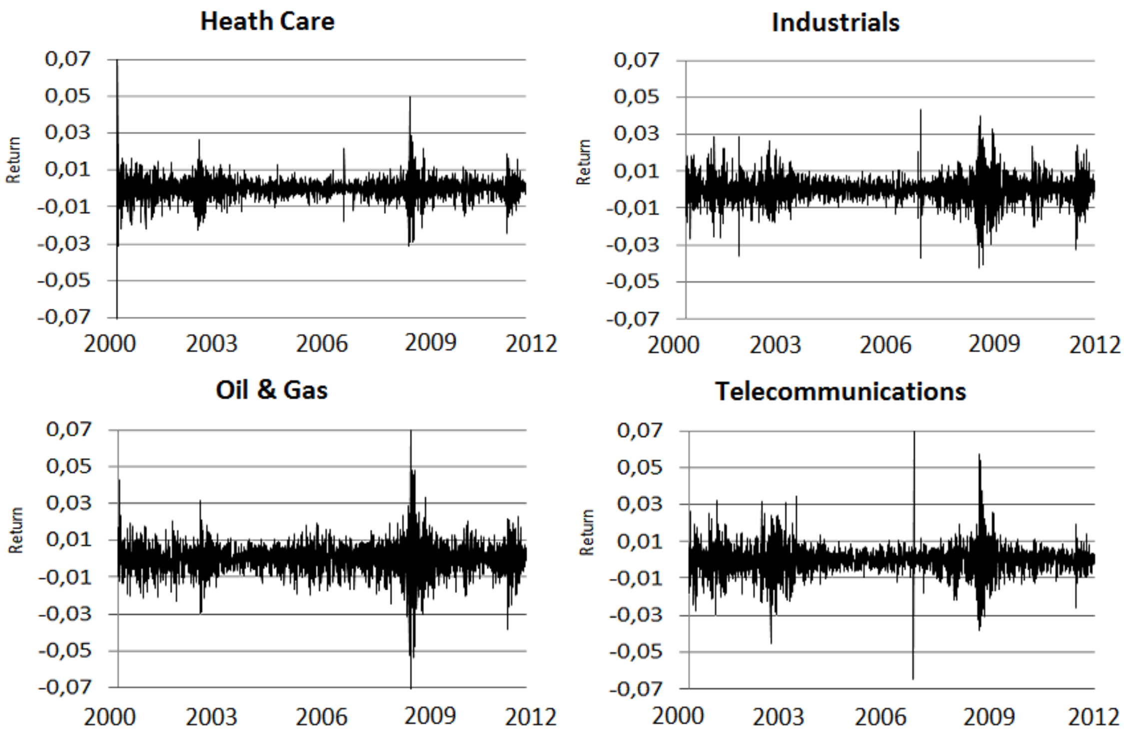

Figure A-2: Sectoral prices

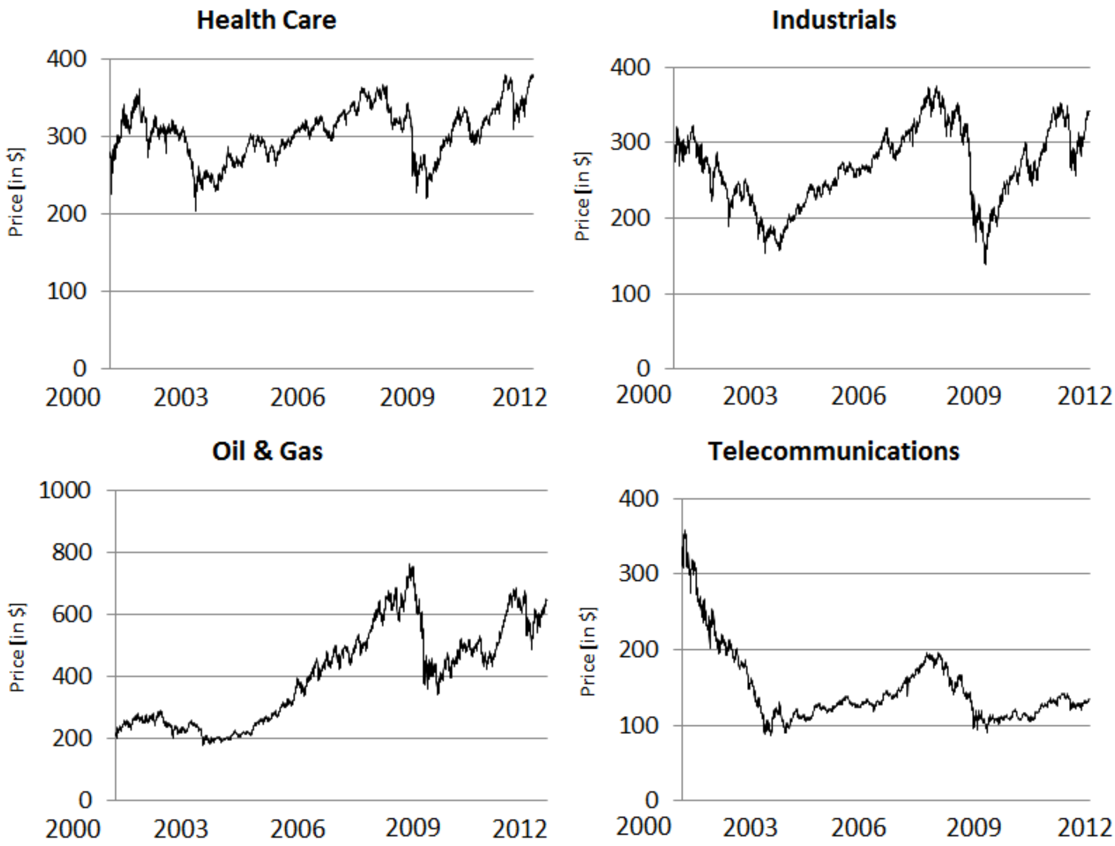

Table A-1: Basic statistics of sectoral indices

Index Name	Ticker	Mean	Variance	Standardized returns	Skewness	Kurtosis
Financials	DJUSFN	-0.0000192	0.0000846	-0.002087	-0.1231621	14.23576
Health Care	DJUSHC	0.0000482	0.0000331	0.008377	-0.3255	30.50289
Industrials	DJUSIN	0.0000286	0.0000475	0.004149	-0.1953193	7.791883
Oil & Gas	DJUSEN	0.0001651	0.0000669	0.020185	-0.3285173	12.33317
Technology	DJUSTC	-0.0000725	0.0000813	-0.00804	0.2696738	7.940238
Telecommunications	DJUSTL	-0.0001327	0.0000528	-0.018262	0.1877542	13.46743

Table A-2: OLS daily statistics summary

		Monday	Tuesday	Wednesday	Thursday	Friday	Lagged returns
S&P 500	Coef.	0.000059	0.00029	0.000093	0.000052	-0.000001	-0.071598
	Std. Dev.	(0.00020)	(0.00019)	(0.00019)	(0.00019)	(0.00019)	(0.01547)
	P value	[0.769]	[0.133]	[0.627]	[0.788]	[0.997]	[0.000]**
S&P 600	Coef.	-0.000244	0.000274	0.000261	0.000176	0.000233	-0.033374
	Std. Dev.	(0.00022)	(0.00021)	(0.00021)	(0.00022)	(0.00022)	(0.01550)
	P value	[0.285]	[0.209]	[0.231]	[0.425]	[0.292]	[0.031]**
DJUSEN	Coef.	0.000106	0.000447	0.000210	-0.000070	0.000157	-0.073776
	Std. Dev.	(0.00034)	(0.00033)	(0.00033)	(0.00033)	(0.00033)	(0.01824)
	P value	[0.756]	[0.176]	[0.524]	[0.832]	[0.636]	[0.000]**
DJUSFN	Coef.	-0.000363	0.000407	0.000095	-0.000001	-0.000270	-0.122889
	Std. Dev.	(0.00038)	(0.00037)	(0.00037)	(0.00037)	(0.00037)	(0.01822)
	P value	[0.345]	[0.273]	[0.798]	[0.962]	[0.470]	[0.000]**
DJUSHC	Coef.	0.000169	0.000262	0.000192	0.000073	-0.000442	-0.093558
	Std. Dev.	(0.00024)	(0.00023)	(0.00023)	(0.00023)	(0.00023)	(0.01822)
	P value	[0.480]	[0.259]	[0.406]	[0.751]	[0.059]	[0.000]**
DJUSIN	Coef.	-0.000116	0.000273	-0.000083	0.000195	-0.000137	-0.047532
	Std. Dev.	(0.00028)	(0.00027)	(0.00027)	(0.00028)	(0.00028)	(0.01828)
	P value	[0.687]	[0.328]	[0.765]	[0.487]	[0.625]	[0.009]**
DJUSTC	Coef.	-0.000157	0.000009	0.000072	0.000412	-0.000722	-0.026665
	Std. Dev.	(0.00037)	(0.00036)	(0.00036)	(0.00036)	(0.00036)	(0.01828)
	P value	[0.676]	[0.981]	[0.842]	[0.262]	[0.050]*	[0.145]
DJUSTL	Coef.	0.000031	0.000224	-0.000406	-0.000118	-0.000403	-0.038670
	Std. Dev.	(0.00030)	(0.00029)	(0.00029)	(0.00029)	(0.00029)	(0.01829)
	P value	[0.919]	[0.446]	[0.166]	[0.690]	[0.175]	[0.035]**

"Coef." denotes average daily return in each day of the week, "Std. Dev." means standard deviation, "P value" denotes p-value for each coefficient and tests the null hypothesis that average daily return is equal to zero.

** We reject the null hypothesis on 5 percent level of significance
* We reject the null hypothesis on 10 percent level of significance

Lowest returns for each index are coloured red.
Highest returns for each index are coloured green.

Table A-3: Monthly statistics summary

		January	February	March	April	May	June	July	August	September	October	November	December	Lagged returns
S&P 500	Coef.	0.0056	-0.0140	0.0346	0.0653	0.0124	-0.0241	-0.0296	-0.0633	0.0083	0.0526	0.1098	0.0794	-0.0273
	Std. Dev.	(0.0490)	(0.0539)	(0.0507)	(0.0537)	(0.0545)	(0.0537)	(0.0499)	(0.0509)	(0.0510)	(0.0475)	(0.0560)	(0.0590)	(0.0171)
	P value	[0.908]	[0.795]	[0.496]	[0.224]	[0.820]	[0.653]	[0.552]	[0.214]	[0.870]	[0.268]	[0.050]*	[0.178]	[0.111]
S&P 600	Coef.	-0.0069	0.0103	0.0387	0.1092	0.0696	0.0132	-0.0584	-0.0275	0.0200	-0.0169	0.1034	0.1163	0.0334
	Std. Dev.	(0.5569)	(0.0576)	(0.0546)	(0.0562)	(0.0572)	(0.0569)	(0.0533)	(0.0558)	(0.0541)	(0.0496)	(0.589)	(0.0576)	(0.0167)
	P value	[0.901]	[0.858]	[0.479]	[0.052]*	[0.224]	[0.816]	[0.272]	[0.621]	[0.710]	[0.732]	[0.079]*	[0.043]**	[0.045]**
DJUSEN	Coef.	-0.0002	0.1098	0.0675	0.0727	0.0327	-0.0359	-0.0368	-0.0257	0.0013	0.0157	0.0419	0.1104	-0.0111
	Std. Dev.	(0.0616)	(0.0693)	(0.0598)	(0.0662)	(0.0620)	(0.0629)	(0.0585)	(0.0610)	(0.0599)	(0.0569)	(0.0648)	(0.0764)	(0.0191)
	P value	[0.997]	[0.114]	[0.259]	[0.272]	[0.598]	[0.568]	[0.529]	[0.674]	[0.982]	[0.782]	[0.518]	[0.149]	[0.561]
DJUSFN	Coef.	-0.0186	-0.0392	0.0327	0.0560	0.0128	-0.1039	-0.0028	-0.0367	-0.0335	0.0231	0.0118	0.1064	-0.0432
	Std. Dev.	(0.0573)	(0.0629)	(0.0590)	(0.0627)	(0.0647)	(0.0604)	(0.0579)	(0.0600)	(0.0550)	(0.0593)	(0.0625)	(0.0753)	(0.0196)
	P value	[0.746]	[0.534]	[0.579]	[0.372]	[0.842]	[0.085]	[0.961]	[0.540]	[0.543]	[0.697]	[0.850]	[0.158]	[0.027]**
DJUSHC	Coef.	-0.0095	-0.0735	-0.0268	0.0528	0.0340	-0.0507	-0.0034	-0.0134	0.0006	-0.0081	0.0430	0.0884	-0.0330
	Std. Dev.	(0.0646)	(0.0636)	(0.0671)	(0.0688)	(0.0664)	(0.0599)	(0.0624)	(0.0639)	(0.0625)	(0.0614)	(0.0625)	(0.0757)	(0.0170)
	P value	[0.882]	[0.247]	[0.689]	[0.443]	[0.609]	[0.397]	[0.956]	[0.834]	[0.992]	[0.895]	[0.491]	[0.243]	[0.052]*
DJUSIN	Coef.	-0.0504	-0.0269	0.0535	0.0768	0.0266	-0.0859	-0.0149	-0.0183	-0.0786	0.0149	0.0899	0.0943	-0.0309
	Std. Dev.	(0.0578)	(0.0626)	(0.0607)	(0.0615)	(0.0639)	(0.0629)	(0.0581)	(0.0620)	(0.0586)	(0.0603)	(0.0659)	(0.0753)	(0.0177)
	P value	[0.383]	[0.667]	[0.378]	[0.212]	[0.677]	[0.172]	[0.797]	[0.767]	[0.180]	[0.805]	[0.172]	[0.210]	[0.081]*
DJUSTC	Coef.	0.0019	-0.0547	0.0214	0.0245	0.0222	-0.0573	0.0034	-0.0067	-0.0592	0.1167	0.0483	0.0070	-0.0166
	Std. Dev.	(0.0578)	(0.0670)	(0.0609)	(0.0616)	(0.0626)	(0.0649)	(0.0593)	(0.0623)	(0.0603)	(0.0580)	(0.0644)	(0.0742)	(0.0201)
	P value	[0.973]	[0.414]	[0.725]	[0.690]	[0.722]	[0.378]	[0.954]	[0.914]	[0.327]	[0.044]**	[0.453]	[0.924]	[0.408]
DJUSTL	Coef.	-0.1142	-0.0447	0.0673	-0.0463	0.0158	-0.0486	-0.0417	-0.0458	-0.0051	-0.0161	-0.0383	0.0940	-0.0127
	Std. Dev.	(0.0605)	(0.0682)	(0.0688)	(0.0669)	(0.0686)	(0.0710)	(0.0615)	(0.0694)	(0.0630)	(0.0656)	(0.0673)	(0.0792)	(0.0144)
	P value	[0.059]*	[0.511]	[0.329]	[0.489]	[0.818]	[0.493]	[0.497]	[0.509]	[0.935]	[0.805]	[0.569]	[0.235]	[0.379]

"Coef." denotes average daily return in each day of the week, "Std. Dev." means standard deviation, "P value" denotes p-value for each coefficient and tests the null hypothesis that average daily return is equal to zero.

** We reject the null hypothesis on 5 percent level of significance
* We reject the null hypothesis on 10 percent level of significance

Lowest returns for each index are coloured red.
Highest returns for each index are coloured green.

Table A-4: OLS monthly statistics summary

		January	February	March	April	May	June	July	August	September	October	November	December	Lagged returns
S&P 500	Coef.	-0.00003	-0.000195	0.000313	0.000517	0.000083	-0.000122	-0.000037	-0.000281	-0.000095	0.0003	0.000404	0.000331	-0.073321
	Std. Dev.	(-0.0003)	(0.00031)	(-0.0003)	(-0.0003)	(-0.0003)	(-0.0003)	(0.00030)	(-0.00029)	(-0.0003)	(-0.00029)	(-0.0003)	(0.00029)	(-0.01548)
	P value	[0.921]	[0.532]	[0.299]	[0.095]	[0.785]	[0.688]	[0.902]	[0.341]	[0.754]	[0.301]	[0.182]	[0.265]	[0.000]**
S&P 600	Coef.	-0.000118	0.000005	0.000305	0.000683	0.000236	0.000032	-0.000243	-0.000186	-0.000029	0.000059	0.000304	0.000714	-0.035915
	Std. Dev.	(-0.00034)	(0.00035)	(-0.00034)	(-0.00035)	(-0.00034)	(-0.00034)	(0.00034)	(-0.00033)	(-0.00034)	(-0.00032)	(-0.00034)	(0.00033)	(-0.01552)
	P value	[0.730]	[0.989]	[0.370]	[0.052]	[0.496]	[0.925]	[0.482]	[0.579]	[0.932]	[0.857]	[0.375]	[0.034]	[0.021]**
DJUSEN	Coef.	-0.000085	0.000452	0.000562	0.000601	0.000246	-0.000223	-0.000166	-0.000122	-0.000187	0.000093	0.000257	0.000663	-0.075394
	Std. Dev.	(-0.00052)	(0.00052)	(-0.00051)	(-0.00051)	(-0.00051)	(-0.00051)	(0.00051)	(-0.0005)	(-0.00052)	(-0.00051)	(-0.00052)	(0.00051)	(-0.01826)
	P value	[0.870]	[0.391]	[0.275]	[0.244]	[0.634]	[0.663]	[0.745]	[0.807]	[0.721]	[0.855]	[0.624]	[0.202]	[0.000]**
DJUSFN	Coef.	-0.000456	-0.000618	0.000602	0.000688	0.000166	-0.000784	0.000272	0.000007	-0.000359	-0.000014	-0.000308	0.000509	-0.125137
	Std. Dev.	(-0.00058)	(0.00059)	(-0.00059)	(-0.00057)	(-0.00058)	(-0.00057)	(0.00057)	(-0.00056)	(-0.00058)	(-0.00057)	(-0.00058)	(0.00058)	(-0.01824)
	P value	[0.435]	[0.296]	[0.315]	[0.234]	[0.774]	[0.171]	[0.634]	[0.990]	[0.543]	[0.979]	[0.599]	[0.381]	[0.000]**
DJUSHC	Coef.	-0.000199	-0.000253	-0.000017	0.000339	0.000171	-0.000129	0.000001	0.000014	-0.000005	-0.000045	0.000253	0.000489	-0.094827
	Std. Dev.	(-0.00036)	(0.00037)	(-0.00036)	(-0.00036)	(-0.00036)	(-0.00035)	(0.00035)	(-0.00035)	(-0.00037)	(-0.00035)	(-0.00036)	(0.00036)	(-0.01825)
	P value	[0.587]	[0.494]	[0.962]	[0.351]	[0.638]	[0.720]	[0.997]	[0.968]	[0.990]	[0.900]	[0.492]	[0.180]	[0.000]**
DJUSIN	Coef.	-0.000299	-0.000254	0.0004	0.000688	0.000047	-0.000479	0.000011	-0.000044	-0.000613	0.000059	0.000382	0.000421	-0.050609
	Std. Dev.	(-0.00044)	(0.00044)	(-0.00043)	(-0.00043)	(-0.00043)	(-0.00043)	(0.00043)	(-0.00042)	(-0.00044)	(-0.00043)	(-0.00044)	(0.00043)	(-0.0183)
	P value	[0.497]	[0.567]	[0.358]	[0.115]	[0.913]	[0.268]	[0.978]	[0.917]	[0.168]	[0.890]	[0.388]	[0.336]	[0.006]**
DJUSTC	Coef.	0.000104	-0.0008	0.000145	0.000326	-0.000021	-0.00029	-0.000146	-0.000049	-0.000974	0.000887	0.000038	-0.000205	-0.02931
	Std. Dev.	(-0.00057)	(0.00058)	(-0.00056)	(-0.00057)	(-0.00057)	(-0.00056)	(0.00056)	(-0.00055)	(-0.00058)	(-0.00056)	(-0.00057)	(0.00057)	(-0.01831)
	P value	[0.856]	[0.170]	[0.799]	[0.567]	[0.970]	[0.608]	[0.795]	[0.929]	[0.094]	[0.116]	[0.947]	[0.720]	[0.110]
DJUSTL	Coef.	-0.000694	-0.000544	0.000453	-0.000184	0.000031	-0.000355	-0.000331	-0.000243	-0.000279	0.000077	0.000112	0.000304	-0.040769
	Std. Dev.	(-0.00046)	(0.00047)	(-0.00045)	(-0.00045)	(-0.00046)	(-0.00045)	(0.00045)	(-0.00044)	(-0.00046)	(-0.00045)	(-0.00046)	(0.00046)	(-0.01831)
	P value	[0.135]	[0.247]	[0.323]	[0.689]	[0.947]	[0.436]	[0.466]	[0.587]	[0.552]	[0.864]	[0.809]	[0.510]	[0.026]**

"Coef." denotes average daily return in each day of the week, "Std. Dev." means standard deviation, "P value" denotes p-value for each coefficient and tests the null hypothesis that average daily return is equal to zero.

** We reject the null hypothesis on 5 percent level of significance
* We reject the null hypothesis on 10 percent level of significance

Lowest returns for each index are coloured red.
Highest returns for each index are coloured green.

Table A-5: OLS part of the month statistics summary

		Part 1	Part 2	Part 3	Part 4	Part 5	Lagged returns
S&P 500	Coef.	0.000468	-0.000292	0.000419	-0.000259	-0.000001	-0.073884
	Std. Dev.	(0.00019)	(0.00019)	(0.00018)	(0.00019)	(0.00019)	(0.01545)
	P value	[0.019]	[0.132]	[0.026]	[0.191]	[0.431]	[0.000]**
S&P 600	Coef.	0.000271	-0.000338	0.000357	-0.000237	0.000669	-0.036960
	Std. Dev.	(0.00022)	(0.00022)	(0.00021)	(0.00022)	(0.00022)	(0.01550)
	P value	[0.230]	[0.124]	[0.095]	[0.290]	[0.003]	[0.017]**
DJUSEN	Coef.	0.000263	-0.000199	0.000285	-0.000020	0.000529	-0.074193
	Std. Dev.	(0.00033)	(0.00033)	(0.00032)	(0.00033)	(0.00033)	(0.01823)
	P value	[0.438]	[0.548]	[0.377]	[0.951]	[0.115]	[0.000]**
DJUSFN	Coef.	0.000064	-0.000456	0.000141	-0.000001	0.000685	-0.125726
	Std. Dev.	(0.00037)	(0.00037)	(0.00036)	(0.00038)	(0.00037)	(0.01823)
	P value	[0.866]	[0.221]	[0.697]	[0.136]	[0.070]	[0.000]**
DJUSHC	Coef.	0.000015	-0.000178	0.000405	-0.000361	0.000346	-0.096165
	Std. Dev.	(0.00023)	(0.00023)	(0.00022)	(0.00023)	(0.00023)	(0.01822)
	P value	[0.950]	[0.443]	[0.074]	[0.128]	[0.142]	[0.000]**
DJUSIN	Coef.	0.000256	-0.000340	0.000252	-0.000390	0.000352	-0.049782
	Std. Dev.	(0.00028)	(0.00028)	(0.00027)	(0.00028)	(0.00028)	(0.01827)
	P value	[0.372]	[0.224]	[0.354]	[0.172]	[0.214]	[0.006]**
DJUSTC	Coef.	0.000439	-0.000399	0.000288	-0.000506	-0.000216	-0.028498
	Std. Dev.	(0.00037)	(0.00036)	(0.00035)	(0.00037)	(0.00037)	(0.01828)
	P value	[0.242]	[0.276]	[0.418]	[0.176]	[0.560]	[0.119]
DJUSTL	Coef.	0.000018	-0.000688	-0.000077	-0.000668	0.000733	-0.044868
	Std. Dev.	(0.00030)	(0.00029)	(0.00028)	(0.00030)	(0.00029)	(0.01832)
	P value	[0.952]	[0.020]	[0.788]	[0.026]	[0.014]	[0.014]**

"Coef." denotes average daily return in each day of the week, "Std. Dev." means standard deviation, "P value" denotes p-value for each coefficient and tests the null hypothesis that average daily return is equal to zero.

** We reject the null hypothesis on 5 percent level of significance
* We reject the null hypothesis on 10 percent level of significance

Lowest returns for each index are coloured red.
Highest returns for each index are coloured green.