Norwegian School of Economics
Bergen, Spring 2020

The Day-of-the-Week Effect at Oslo Stock Exchange

Examining the presence of, and explanations for, the Day-of-the-Week effect in Norway from 2000 to 2019

Håvard Flostrand and Eirik Fløgstad

Supervisor: Darya Yuferova

Master thesis, Economics and Business Administration

Majors: Financial Economics and Business Analytics

NORWEGIAN SCHOOL OF ECONOMICS

Abstract

We study the Day-of-the-Week effect in the Norwegian securities market from 2000 to 2019, in which we examine whether daily returns are lower on Monday and higher on Friday than the other days of the week. We find evidence suggesting that such an anomaly does exist, in which Monday returns are 0.059 percentage points lower, and Friday returns are 0.23 percentage points higher than the other days of the week. We further test whether this phenomenon can be explained by differences in calendar settlement time, changes in investor sentiment or speculative short seller activity. Our findings suggest that increased investor sentiment from Thursday to Friday, as well as the closing of speculative short positions on Fridays, may contribute to the Day-of-the-Week effect in the Norwegian securities market.

Keywords:
Day-of-the-Week effect, market anomaly, settlement time, investor sentiment, speculative short interest

Acknowledgements

This master thesis constitutes 30 ECTS of our respective Master of Science degrees in Financial Economics and Business Analytics at the Norwegian School of Economics. The work has been challenging, yet very fulfilling. We would like to express our sincere gratitude to our supervisor, Assistant Professor of Finance, Darya Yuferova, for contributing with valuable input and rewarding discussions on the topic. We would further like to thank our friends, families and partners for their support throughout the semester.

Eirik Fløgstad

Håvard Flostrand

Contents

List of Tables

List of Figures

1. Introduction

The goal of this thesis is to examine the presence of, and possible explanations for, the Day-of-the-Week effect in the Norwegian securities market. This is done by utilizing panel data for Norwegian public companies from January 2000 to December 2019. We first establish the presence of the effect before turning to possible explanations. The premise that some days exhibit significantly higher or lower returns than others is, in large part, an unexplained phenomenon, but several hypotheses are suggested in the existing literature. The hypotheses that are examined in this thesis are the *sentiment-*, *settlement time-* and *speculative short interest hypothesis*.

In recent years, the validity of the efficient market hypothesis (EMH) has been scrutinized, as evidence has been documented in favor of the presence of market anomalies (Bodie, Kane & Marcus, 2018). The Day-of-the-Week effect is such an anomaly. Research into the Day-of-the-Week effect has shown that Monday returns tend to be lower, and Friday returns to be higher than the other days of the week (Apolinario et al., 2006; French, 1980). Our research finds evidence in favor of a Day-of-the-Week effect at Oslo Stocks Exchange over the last 20 years, defined as lower daily returns on Mondays and higher daily returns on Fridays, relative to the other days of the week. We find that the mean daily return on Mondays is -0.011%, which is 0.059 percentage points lower than the other days of the week. The mean daily Friday return is 0.28%, and 0.23 percentage points higher than the other days of the week. In the existing literature, Friday returns minus the following Monday returns are often referred to as "The Weekend Effect". Our evidence therefore suggests that the mean Weekend Effect in Norway over the last 20 years is 0.29%[1]. Chen & Singal (2003) find that the equally weighted average Weekend Effect in the US of all ordinary common shares traded on NYSE, AMEX and Nasdaq from 1962 to 1999 is 0.338%. Over the last ten-year period, from 1990 to 1999, the effect was 0.28%. Dubois & Louvet (1996) study the effect for several countries, and find that for European markets from 1969 to 1992, the Weekend Effect was approximately 0.15%,

[1] We calculate The Weekend Effect as the mean Friday return minus the mean Monday return.

0.096%, 0.176% and 0.228% for Germany, France, UK and Switzerland respectively. In magnitude, the identified effect in Norway is therefore closer to that of the US markets.

Several theories have been suggested as to why the Day-of-the-Week pattern exists. Our thesis explores prevalent theorized explanations for the effect in recent academic research. By doing so, we aim to determine which factors may drive the observed effect. To the best of our knowledge, little or no research has previously focused on the presence of, and explanations for, the effect in the Norwegian securities markets. Exploring these research questions is therefore the main novelty of our thesis.

The sentiment hypothesis states that the Day-of-the-Week effects are caused by changes in the mood of investors[2]. When investor sentiment increases from Thursday to Friday and decreases from Friday to Monday, Fridays yield higher, and Mondays yield lower daily returns than the other days of the week. This happens as sentiment influences investor psychology, which affects prices. When there is an exogenous factor, like the calendar, affecting sentiment, systematic patterns in securities prices emerge. If the driving force behind the anomaly is investor sentiment, Birru (2018) further argues that the anomaly will be most apparent for stocks that exhibit more sensitivity to such changes in investor sentiment. Baker and Wurgler (2006) argue that stocks with more subjective valuations or that are harder to arbitrage will exhibit such an increased sensitivity to sentiment. To examine this hypothesis, Birru (2018) identifies several firm-specific characteristics that should render securities more sensitive to changes in investor sentiment. We use nine of these; *beta, price, size, illiquidity, 52-week high, maximum return, earnings, return on assets and age.* By studying how these factors affect daily returns on Mondays and Fridays, compared to the other days of the week, we can determine whether sentiment may partly explain the observed effect. We find that the effect of the age, earnings and price characteristics of the firms impact daily returns on Fridays and

[2] Birru 2018; Zilca 2017 and Rystrom & Benson 1989 all argue that the Day-of-the-Week effect may be caused by changes in investor sentiment.

Mondays differently than on the other days of the week. Firms that are young, have negative earnings and are low-priced exhibit higher daily returns on Fridays and/or lower daily returns on Mondays relative to the other days. Birru (2018) finds that sentiment sensitive stocks yield low daily returns on Mondays and high daily returns on Fridays, relative to sentiment insensitive stocks, for all the nine mentioned traits. However, we argue that these findings may be due to a high degree of correlation between the traits, and that we are able to uniquely identify which of the traits that drive the sentiment sensitivity of the stocks. We further generate an aggregate sentiment score, and find that stocks with a maximum sentiment sensitivity score exhibit 0.61 percentage points higher Friday returns than stocks with a minimum score of sentiment sensitivity. To the best of our knowledge, no similar approach has been pursued in the study of behavioral explanations for the Day-of-the-Week effect.

The settlement time hypothesis states that as stock transactions are traditionally settled a certain amount of business days after the transaction, stocks sold on Fridays have a longer settlement period in calendar days than stocks sold on Mondays. Therefore, Friday transactions include a higher cost of carry for the seller, causing Friday returns to be higher than Monday returns. In 2014, the settlement time in Norway was reduced from *T+3* to *T+2*. This constitutes a natural experiment for studying whether this change in settlement time affected Monday and Friday returns differently than the other days. The findings do not, however, suggest that differences in calendar settlement time explain the observed Day-of-the-Week effect in Norway.

The speculative short interest hypothesis suggests that speculative short sales affect price formation around the weekend (Chen & Singal, 2003). If investors shy the premise of holding speculative short positions outside trading hours, the weekend may represent a natural breakpoint for closing such positions. Speculative short sellers may, therefore, buy back stocks on Fridays and sell short on Mondays. This would cause Friday demand and Monday supply to be higher than on other days, contributing to higher Friday, and lower Monday returns. Using actively traded put options as a proxy for reduced speculative short sales, we find that the effect on daily returns of having actively traded put options is lower on Fridays relative to the other days of the week. In fact, the effect of a stock having actively traded put options, on returns, is 0.05 percentage points lower on Fridays relative to the other days of the week. This is consistent with Chen & Singal's (2003) findings, namely that stocks with listed options exhibit a 16% lower Weekend Effect than stocks without them. However, we argue that the availability of put options may be correlated with other factors that affect daily returns. Comparing the effect of put-availability on Fridays and Mondays to the other days of the week, allows us to isolate the effect.

In summary, we identify the presence of a Day-of-the-Week effect in the Norwegian securities market. Further, we identify that increased investor sentiment from Thursday to Friday, as well as the role of speculative short sellers, may explain some of the observed effect. However, we do not claim that there are exploitable arbitrage opportunities by short selling stocks on Mondays and buying stocks on Fridays, as the transaction costs associated with this are likely too large. The evidence does suggest that the Norwegian securities market may not be perfectly rational, to the extent that changes in investor sentiment may explain why daily returns on some days are higher than on others. This also suggests, at least partly, that the Day-of-the-Week effect in Norway is an anomaly.

The remainder of the thesis is structured as follows. Part two presents and discusses the theoretical framework and literature review. The third part presents and describes the data, and the fourth part gives an overview of the methodology. Part five presents our main findings before we summarize the thesis in part six.

2. Theoretical Framework

We start by introducing the main theoretical framework, followed by a discussion of existing academic literature and empirical findings. First, we introduce the efficient market hypothesis and the Day-of-the-Week effect (DOW-effect). Second, we discuss several hypothesized explanations for the anomaly. This discussion emphasizes the *sentiment-*, *settlement time-* and *short interest hypotheses*, for each of which we present our formal hypotheses.

2.1 The Day-of-the-Week Effect

Kendell (1952) was among the first to examine economic time-series using computers. He found, somewhat surprisingly at the time, no predictable patterns in stock prices; that prices behave "*almost like a wandering series*". In retrospect, his findings are argued to be evidence of efficient markets; markets in which rational investors price securities based on all *available* relevant information (Bodie, et al., 2018). This is known as the efficient market hypothesis.

There are three different forms of the EMH, regarding what is considered "all available information" (Bodie, et al., 2018). The weak form states that current prices reflect all information from historical prices. The semi-strong form states that as well as reflecting information from historical prices, current prices also reflect all publicly available information. In the strong form, all private information should also be reflected in current prices. The premise that by studying publicly available information, one can earn abnormal risk-adjusted returns, are contradictions to the semi-strong form of the EMH and are therefore considered market anomalies. Such anomalies are documented thoroughly in the existing literature.[3] The issue with considering many of these findings as contradictions to the EMH,

[3] Examples of the more known anomalies are the small size anomaly discovered by Banz (1981), and the high ratio of book value to market value anomaly discovered by Rosenberg, Reid, and Lanstein (1985)

is that a test of efficient markets is simultaneously a test of the risk adjustment process. Therefore, one cannot categorically conclude that the findings are contradictions to efficient markets, because the effects might also capture risk-adjustments not included in the capital asset pricing model (Bodie, et al., 2018). However, the DOW-effect can hardly be argued to capture risk-adjustments and is argued to include behavioral and psychological elements[4].

Stock market returns have historically been found to systematically differ based on the day of the week. Monday returns have been found to be lower, and Friday returns higher, than the other days of the week. The first mention of the effect was by Kelly (1930), in his book *"Why you win or lose: the psychology of speculation".* In which he claims that Monday returns are lower than the other days of the week[5]. Another practitioner, Cross (1973) focused on pairs of Mondays and Fridays, and not the rest of the week. He found that from 1953 to 1970, the mean returns were significantly higher on Fridays than on Mondays, for every year in the time period. He also found a statistically significant positive relationship between Monday returns and the direction of returns on the preceding Friday.

French (1980) was amongst the first in academic circles to study the effect. He found that Monday returns for the Standard and Poor´s composite portfolio were negative, while Tuesday through Friday returns were positive. Gibbons and Hess (1981) conducted similar research and found that the S&P 500 had persistently negative mean returns on Mondays. Conolly (1989) also found evidence of the effect but concluded that the effect disappeared in the US after 1975. Both French (1980) and Connolly (1989) argue that after controlling for transaction costs, there are no exploitable arbitrage opportunities. Thus, they argue that their findings are consistent with efficient markets. Most of the existing literature finds that Monday returns tend

[4] Rystrom and Benson (1989) were among the first researchers to argue that the effect may be driven by psychological elements.

[5] Kelly refers to a three-year statistical study, covering the Dow-Jones index, in which the index increases with an average of 56 cents on 71 Mondays, and decreases with an average of 96 cents on 77 Mondays. It should be noted that Kelly does not state where this study originates.

to be lower, and/or that Friday returns tend to be higher, than the other days of the week. However, the effect is not necessarily constrained to these two days (Keim & Stambaugh, 1984). The focus of our thesis is nevertheless solely on Monday and Friday returns. To examine the presence of the DOW-effect in the Norwegian securities market, we test the following hypothesis:

H1: Daily returns are lower on Mondays, and higher on Fridays, than the other days of the week.

Several explanations are suggested as to why the DOW-effect exists. French (1980) argues that if stock returns are generated over calendar time, Monday returns should be three times higher than the other days of the week[6]. Or, if returns are generated over trading time, all the days of the week should exhibit similar returns. Either way, there is no immediate intuitive reason for why Monday returns should be lower, and Friday returns higher, than the other days of the week. A possible explanation is a systematic variation in institutional trading behavior by the day of the week. If institutional traders are less active on Mondays than on the other days of the week, lower Monday returns could be due to inelasticity of demand (Dubois & Louvet, 1996). Lower Monday returns are further argued to be caused by systematic differences in news release days based on news content. If bad news is systematically released from Friday close to Monday open, and good news from Thursday close to Friday open, this could be a rational explanation for the observed DOW-effect (Birru, 2018). However, French (1980) argues that efficient markets would not exhibit systematic differences in returns, based on systematic differences in news release dates. Instead, efficient markets would expect negative news releases over the weekend, and discount prices appropriately during the week.

[6] The returns should be three times higher because Monday should account for the effect of Saturday and Sunday as well.

Our thesis focuses on the three previously mentioned hypothesized explanations of the DOW-effect. Namely the *sentiment-*, *settlement time* and *short interest hypotheses*. In the next three segments, these are explained in further detail.

2.1.1 Sentiment Hypothesis

The efficient market hypothesis leaves no room for investor sentiment or irrationality of agents. However, investor sentiment and stock prices have been found to have a statistically significant relationship (Baker & Wurgler, 2006; Fisher & Statman, 2000). In the psychological literature, mood is documented to be high on Fridays relative to Mondays through Thursdays (Egloff, et al., 1995; Reid, et al., 2000). This means that mood increases from Thursday to Friday and decreases from Friday to Monday. Furthermore, evidence from the literature suggests that when sentiment is high (low), people tend to evaluate prospects more positively (negatively) (Wright & Bower, 1992). Therefore, a proposed explanation for the Day-of-the-Week effect is behavioral (Birru, 2018; Zilca, 2017; Rystrom & Benson, 1989). The hypothesis states that as sentiment increases from Thursday close to Friday open, investors may evaluate future uncertain prospects more positively. Investors thus place a higher valuation on stocks, which thereby increases returns. The same applies in the opposite direction; as sentiment decreases from Friday close to Monday open, evaluations of prospects are reduced and returns decrease.

Under the sentiment hypothesis, the anomaly results should be clearest for stocks that are more sensitive to such changes in sentiment. Evidence in psychological literature suggests that the effect of mood on decision-making is conditional on the traits of the object being evaluated (Birru, 2018). Sentiment also has a stronger effect on decision-making when little information about the evaluated object is available (Clore, et al., 1994, p. 386). Therefore, stocks with highly subjective valuations will exhibit more sensitivity to changes in sentiment. Baker & Wurgler (2006) argue that these include small, young, highly volatile, unprofitable and distressed stocks. Birru (2018) extends these traits to stocks that have lottery-like properties and great limits to arbitrage. Under the sentiment hypothesis, stocks exhibiting the mentioned qualities should exhibit lower Monday, and higher Friday returns, than the other days of the week, than firms without the increased sentiment sensitivity. Birru (2018) finds that such speculative stocks yield low Monday and high Friday returns, compared to non-speculative stocks. Based on these proposed effects, we test the following two hypotheses:

H2: Sentiment sensitive firms exhibit higher Friday and lower Monday returns than sentiment insensitive firms.

H3: Sentiment sensitive firms exhibit higher daily returns on Fridays, and lower daily returns on Mondays, relative to the other days of the week.

2.1.2 Settlement Time Hypothesis

Dobois & Louvet (1996) argue that settlement time can influence returns, as the settlement period is traditionally a certain amount of bank days after the transaction. Therefore, Gibbons & Hess (1981) argue that quoted prices for stocks are forward- and not spot prices. Since transactions done on Fridays have more settlement days (in calendar time) than Mondays, the cost of carry, or "*forward-premium*", is larger for transactions done on Fridays than it is for those done on Mondays. Sellers will consequently demand a marginally higher price for stocks sold on days that have settlement days after the weekend. Buyers may also be willing to pay the marginally higher price, as they have more days of alternative interest income before the settlement day (Gayaker, et al., 2020). This further means that selling will, all else equal, be more favorable on certain days. When the settlement period is *T+3*, this means that transactions done on Wednesday, Thursday and Friday have a 5-day settlement period (transactions are respectively settled on Monday, Tuesday and Wednesday), while transactions done on Monday and Tuesday have a 3-day settlement period (transactions are respectively settled on Thursday and Friday).

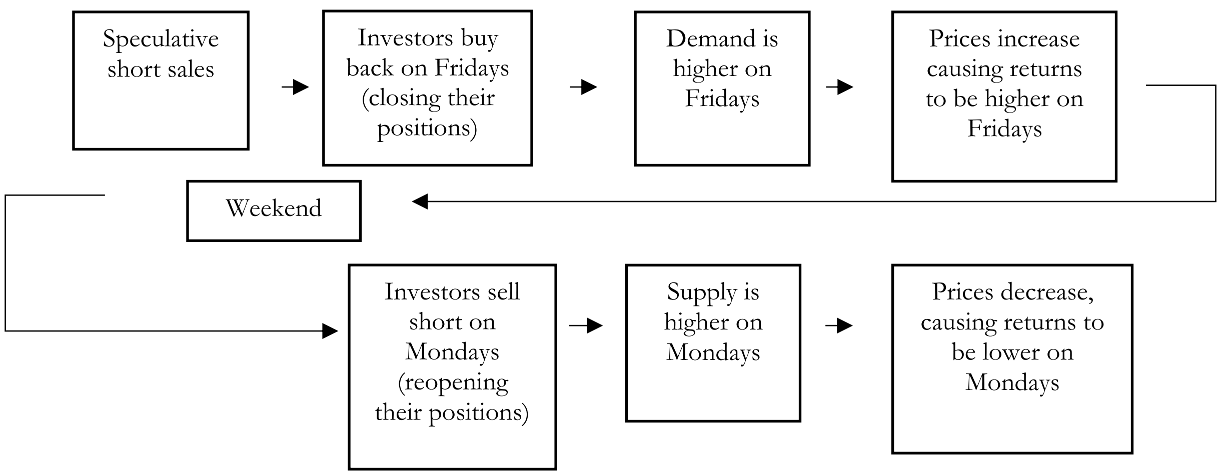
Although market microstructures, such as the *settlement time hypothesis*, are one of the more researched theories of the Day-of-the-Week effect, the results are ambiguous. Dobois & Louvet (1996) find evidence of a DOW-effect for major indices in nine countries, after controlling for differences in settlement time. Clare et al. (1998), however, find that after a change in settlement procedures for the Kuala Lumpur stock exchange, which reduced the settlement time differences, most of the variation in daily stock returns disappeared. To examine whether differences in settlement time may contribute to the DOW-effect in Norway, the following hypothesis is tested:

H4: A reduction in settlement time decreases Friday returns and increases Monday returns.

2.1.3 Speculative Short Interest Hypothesis

Chen & Singal (2003) argue that investors tend to close speculative short positions on Fridays and re-open them on Mondays. This is due to the increased risk of having short positions, especially when the investor is unable to trade for a longer time period, such as the weekend. Therefore, demand increases on Fridays, and supply increases on Mondays, as investors close and re-open positions respectively on these days. This causes daily returns to be higher on Friday, and lower on Monday, than the other days of the week. The effects causing speculative short interest to contribute to the Day-of-the-Week effect are summarized below.

Figure 2-1 - Speculative Short Interest Mechanisms



Accordingly, Chen & Singal (2003) argue that stocks with high speculative short interest have higher Friday and lower Monday returns than stocks with low short interest. They further argue that the amount of speculative short sales can be captured by the availability of actively traded put options. Because the loss on a put option is limited to the premium, and not theoretically unlimited as with short sales, they argue that speculative short sellers will prefer put options over short sales. All else equal, one can therefore capture the effect of speculative short sales by using the availability of actively traded put options as a proxy for *less* speculative short sales. Chen & Singal (2003) further note that put options introduce a second party, namely the put writer, who often tends to hedge the written put with a call option and/or short sale of the same asset. The risk of this position, however, is not the same as for a non-hedged open short position, and therefore does not require the same close monitoring. As such, these positions do not have the same need to be closed and re-opened around the weekend. Thus, stocks with actively traded put options available will exhibit lower Friday and higher Monday returns, relative to the other days of the week. Chen & Singal (2003) find that stocks with high short interest exhibit a higher Weekend Effect[7] than stocks with low short interest, and that stocks with available put options exhibit a decreased Weekend Effect. To test for whether speculative short-interest contributes to the DOW-effect in Norway, the following hypothesis is tested:

H5: The availability of put options is associated with lower daily returns on Friday, and higher daily returns on Monday, relative to the other days of the week.

2.1.4 Comparative Equation

After testing the hypothesized explanations for the DOW-effect, we compare the hypotheses against each other. This allows us to test which of the effects are the most prominent and whether there is a degree of omitted variable bias in any of the individual equations. To do

[7] They define the Weekend Effect as Friday returns minus Monday returns.

this, we create an equation that includes the variables from the *speculative short interest*, *sentiment* and *settlement time* hypotheses.

Following our introduction of the main theoretical framework and discussion of existing academic literature and hypothesized explanations, we will now focus on the data that forms the foundation for our research.

3. Data

In this part, the data used in the analysis is introduced. We mainly use data from the Compustat database and derivatives statistics from Oslo Børs to create our panel dataset. Firstly, some summary statistics are introduced, before we turn to the calculation of daily returns, the firm-specific characteristics used and the put option availability.

Table 3-1 - Descriptive Statistics

Table 3-1 presents the descriptive statistics for all relevant variables in the dataset, consisting of the number of observations, mean values, standard deviations, minimum and maximum values. *PriceClose* is the daily closing price for each stock. *Returns* are daily returns in percentages. *Beta* is the one-year monthly betas of the firms. *ROA* is return on assets. *Price* is the stock price in the last trading day of the calendar year. *Size* is the market capitalization. *Earnings* is a binary variable with a value of 1 for firms with positive earnings. *Age* is defined as the amount of years since the firms first appearance in the Compustat database. *MaxReturn* is the maximum return in the previous month. *Illiquidity* is calculated as absolute daily stock return divided by daily NOK trade volume. *52 Week High* is calculated as the highest closing price in the previous 52-week period, divided by the closing price of the last observation of the previous month. *SentimentScore* is an average score of sentiment sensitivity.

Variable	Obs	Mean	Std.Dev.	Min	Max
PriceClose	553000	61.764	161.477	.002	4900
Returns	553000	.085	7.39	-90.2	2882.8
Beta	536000	.732	.619	-1.176	3.442
ROA	422000	-.012	.072	-.392	.135
Price	511000	61.579	159.878	.006	3160
Size	511000	1.01e+10	4.37e+10	219000	6.12e+11
Earnings	544000	.574	.495	0	1
Age	547000	10.365	12.809	0	110
MaxReturn	547000	.079	.238	-.852	28.828
Illiquidity	508000	8.02e-06	.000248	5.44e-12	.03485
52WeekHigh	547000	2.168	5.05	1	400
SentimentScore	400000	5.334	1.752	1.667	9.889

3.1 Compustat Data

Daily closing prices for firms listed on Oslo Børs and Oslo Axess are gathered from Compustat Capital IQ – Daily Global. For firms with multiple share classes, only A-class shares are kept in the data. Due to the use of balance sheet information in calculation of the firm-specific factors, financial firms are excluded. After excluding financial firms, firms not incorporated in Norway and firms for which there is no data available, the dataset consists of 391 firms. These include firms that have been listed at some point in time between 2000 and 2019.

Daily returns are calculated as $Return_t = ((Close\ Price_t - Close\ Price_{t-1})/Close\ Price_{t-1}) \times 100$. Since some stocks are highly illiquid, to the point where traded volume is zero on some active trading days, both the closing price on day *t* and on day *t-1* are required to calculate returns. If the stock is not traded on either day *t* or day *t-1*, returns on day *t* are treated as missing. As the anomaly in question is based on daily returns, and possibly a change in investor sentiment from Friday to Monday, we must be careful not to contribute an effect of day *t-1* to day *t*. Furthermore, corporate actions affecting shares outstanding often have a mechanical effect on stock prices. Actions like stock-splits, stock buybacks and stock issues influence the number of shares outstanding, and therefore have such an effect. All daily returns, on the first trading day, following a change in the number of shares outstanding are removed, thus removing most outliers in the data. After controlling for this, the data consists of 553 181 observations of daily stock returns.

3.1.1 Firm Characteristics

We now turn to the theoretical foundation for how each firm characteristic is related to sentiment sensitivity, as well as the calculation methods for these characteristics. The firm-specific variables in question are mainly motivated by Baker & Wurgler (2006) and Birru (2018). The nine selected traits are based on availability of data about Norwegian stocks and a selection of characteristics that we want to examine. Table 3-2 below summarizes all nine firm specific variables and their relevance for sentiment sensitivity. The traits differ in frequency of rebalancing, varying between monthly, quarterly and yearly. For most of the characteristics, several observations are required for their calculation.

Table 3-2 - Summary of Firm Characteristics

Table 3-2 summarizes which firm specific traits are associated with which sentiment sensitive variable.

Trait	Variable
Lottery	Maximum Return and Price
Young	Age
Unprofitable	ROA and Earnings
Speculative demand	52-Week High and Beta
Limits to arbitrage	Size and Illiquidity

Maximum Return and Price

Kumar (2009) finds that stocks with lottery-like properties have more speculative demand and are therefore more sensitive to sentiment. This effect is driven by low-income individual investors who have portfolios with an overweight of lottery-like stocks. Birru (2018) uses the price and the maximum return of a stock as proxies for stocks with lottery-like properties. *Stocks with high maximum returns and stocks with low prices should therefore be more sensitive to changes in sentiment, relative to stocks with low maximum returns and high prices.*

Following Bali et al. (2011), maximum return is defined as the highest return in month *t-1*. Portfolios are rebalanced monthly based on the maximum return of the previous month.

Based on Birru (2018), price is defined as the stock price in the last trading day of the calendar year. Portfolios are rebalanced yearly based on the last stock price observation from year *t-1*.

Age

Baker & Wurgler (2006) argue that age and sensitivity to sentiment are correlated. Because of the lack of historical information about young firms, the propensity to speculate in these stocks is higher than for older stocks. As the propensity to speculate is affected by changes in investor sentiment, they argue that young firms exhibit increased sensitivity to changes in sentiment.

Young stocks should therefore be more sensitive to changes in investor sentiment than older stocks.

Based on Baker & Wurgler (2006), age is defined as the amount of years since the firms first appearance in the Compustat database. Portfolios are rebalanced at the start of the calendar year, based on the current year minus the year of the IPO. For firms with IPO dates from 1986, we find the IPO date using the first observation of the firm in the Compustat database. For firms with IPO dates prior to 1986, we find the IPO dates manually. For some of the firms, we are unable to find information about the IPO date. Because of this, the age variable suffers from selection bias, as the age of some older firms are missing.

ROA and Earnings

Unprofitable firms tend to be harder to value and to have more subjective valuations (Baker & Wurgler 2006). *Stocks with low ROA and negative earnings should therefore exhibit more sensitivity to changes in sentiment than firms with high ROA and positive earnings.*

Following Birru (2018), earnings is defined as income before extraordinary items, Compustat yearly item IB. From this, we generate a binary variable. The variable takes a value of one if the firm has positive earnings in year *t-1*, and zero otherwise. Portfolios are rebalanced at the start of the calendar year, based on the earnings in year *t-1*.

Following Hou et al. (2015), return on assets (ROA) is defined as income before extraordinary items, Compustat quarterly item IBQ, divided by one quarter lagged total assets, Compustat quarterly item ATQ. For quarter *t*, the quarterly ROA is IBQ_{t-1} divided by ATQ_{t-2}. Portfolios are rebalanced quarterly. ROA is winsorized at the top and bottom 1% of the observations.

52-Week High

Hao, et al. (2018) find a strong relationship between 52-week high and sensitivity to sentiment, and that stocks far from their 52-week high exhibit more sensitivity to changes in sentiment than stocks closer to their 52-week high. *Stocks far from their 52-week high should therefore be more sensitive to changes in sentiment than stocks close to their 52-week high.*

Following Birru (2018), a stocks distance from its 52-week high is calculated as the highest closing price in the previous 52-week period, divided by the closing price of the last observation of month *t-1*. Portfolios are rebalanced monthly.

Beta

High beta stocks are found to have a higher propensity for speculation than low beta stocks (Antoniou, et al., 2016). *Stocks with high betas should therefore be more sensitive to changes in sentiment than stocks with low betas*.

The beta values of the stocks are calculated as one-year monthly betas, in which beta is the regression coefficient of market excess return on stock excess return. Market return is that of the OSEBX index, gathered from Oslo Børs (2020). The risk-free rate is the yearly average, calculated daily, return of 10-year government bonds (Norges Bank n.d.). Following Birru (2018), a minimum of 30 observations are required for calculating beta, and portfolios are rebalanced monthly based on the beta of month *t-1*. Beta is winsorized at the top and bottom 1% of the observations.

Size and Illiquidity

Baker & Wurgler (2006) argue that small firms tend to have greater limitations to arbitrage, and that firms with limits to arbitrage have a higher sensitivity to changes in sentiment. They argue that the limitations to arbitrage arise from a high degree of idiosyncratic risk for small firms, making arbitrage especially risky. Furthermore, small and illiquid stocks are often harder to trade and more expensive (and sometimes impossible) to sell short (Baker & Wurgler, 2006). *Small and illiquid stocks should therefore exhibit more sensitivity to changes in sentiment than larger and liquid stocks.*

Based on Birru (2018), size is defined as a firm's market capitalization at the end of year *t-1*. Market capitalization is calculated as shares outstanding multiplied by the share price from the last observation in year *t-1*. Portfolios are rebalanced yearly.

Following Amihud (2002) illiquidity is calculated as absolute daily stock return divided by daily NOK trade volume. Thus, liquid stocks will have small values using this illiquidity measure, and illiquid stocks will have larger values. The portfolios are rebalanced monthly based on the average daily illiquidity of month *t-6* to month *t-1*. In measuring the average illiquidity, the measure for days with a return of zero is treated as missing. This is due to such great illiquidity among many of the illiquid firms, that there are some occurrences of no change in closing price, even when traded volume is greater than zero. Using this measure of illiquidity, such occurrences give illiquidity a value of zero. Thus, for the illiquid firms, the average would be distorted downwards, yielding inaccurate representations of the actual illiquidity.

Aggregate Sentiment Score

From the nine firm characteristics, we further create an aggregate score of sentiment sensitivity. The nine firm specific characteristics are given a score from 1 to 10 based on their sensitivity to sentiment, in which a score of 1 indicates low sensitivity to changes in investor sentiment, and a score of 10 indicates high sensitivity to changes in investor sentiment. For each month, percentiles are calculated for each characteristic, and values are given to each firm-trait based on these. The aggregate sentiment score is then calculated as the average of the characteristics scores. If there is not a minimum of five individual characteristic observations, for each month and firm, the score is not calculated. This is done to avoid spurious scores.

3.2 Short-Interest Data

Motivated by Chen & Singal (2003), we use actively traded put options as a proxy for *less* speculative short sales. As speculative short sellers may prefer put options to short sales, because of the lower risk associated with these, they argue that such stocks will have *less* speculative short sales, as discussed in section 2. Therefore, the Day-of-the-Week effect, in terms of higher Friday and lower Monday returns, should be smaller for stocks with actively traded put options. Using Oslo Børs derivatives statistics (n.d.), we generate a variable with a value of 1 if a stock has actively traded put options during year *t*, and 0 otherwise. We use dummy variables instead of relative option volume, as relatively few companies have actively traded puts each year[8].

[8] Approximately 9.3% of the company-date observations have actively traded put options (PutsDummy = 1).

4. Methodology

We now turn to the methodology of the thesis. In this segment, we present and explain the equations, before commenting on the choice of estimation models and their underlying assumptions.

4.1 Equations

In all the regressions, the intercept is denoted as $\boldsymbol{\beta_0}$, the coefficients for the independent variables are denoted as $\boldsymbol{\beta_1}, \boldsymbol{\beta_2}, \ldots, \boldsymbol{\beta_N}$ and the error term is denoted as $\boldsymbol{V_{it}}$. The five equations allow us to test the following five hypotheses; whether daily returns are lower on Mondays, and higher on Fridays than the other days of the week (H1). If sentiment sensitive firms exhibit higher Friday and lower Monday returns than sentiment insensitive firms (H2). The possibility that sentiment sensitive firms may exhibit higher daily returns on Fridays, and lower daily returns on Mondays, relative to the other days of the week (H3). Whether a reduction in settlement time decreases Friday returns and increases Monday returns (H4). And lastly, whether the availability of put options is associated with lower daily returns on Friday, and higher daily returns on Monday, relative to the other days of the week (H5). Following this short summary of the hypotheses, we present the equations and their expected coefficient values below.

4.1.1 Equation 1 – The Day-of-the-Week Effect

To test for the presence of a general DOW-effect (H1) in Norway, we propose the following equation.

$$Returns_{it} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Monday_t + \boldsymbol{\beta_2} Friday_t + V_{it}$$

The Monday coefficient represents the effect of the day being Monday on daily returns. A coefficient lower (higher) than zero indicates that Monday returns are lower (higher) than the other days of the week. The same applies for Friday. In this equation, if the DOW-effect is present in the Norwegian securities market, we would expect $\boldsymbol{\beta_1}$ to be negative, and $\boldsymbol{\beta_2}$ to be positive.

4.1.2 Equations 2 and 3 – The Sentiment Hypothesis

To test the *sentiment hypothesis*, we first test whether the effect on daily returns of increased sentiment sensitivity is lower on Monday and higher on Friday than other days of the week. We must also test whether sentiment sensitive stocks exhibit higher Friday and lower Monday returns than sentiment insensitive stocks. Therefore, we propose the following equation.

$$\begin{aligned} Returns_{it} = \boldsymbol{\beta_0} + \ & \boldsymbol{\beta_1} Monday_t + \boldsymbol{\beta_2} SentimentScore_{it} \\ & + \boldsymbol{\beta_3} Monday_t * SentimentScore_{it} + \boldsymbol{\beta_4} Friday_t \\ & + \boldsymbol{\beta_5} Friday_t * SentimentScore_{it} + V_{it} \end{aligned}$$

In which we expect $\boldsymbol{\beta_3}$ to be negative, indicating that relative to the other days, increased sentiment sensitivity decreases Monday returns. Under the sentiment hypothesis, we would also expect $\boldsymbol{\beta_5}$ to be positive, indicating that relative to the other days, increased sentiment sensitivity increases Friday returns. Further, we reparametrize to find the main effect of our sentiment score on Monday and Friday returns respectively. Again, we would expect the effect of the sentiment score on Friday returns to be positive, and vice versa for Mondays.

In the third equation, the focus is on the effects of each individual sentiment sensitive firm characteristic on Monday and Friday returns. The aim here is to explore whether we can identify which of the sentiment characteristics affect returns differently on Mondays and Fridays relative to the other days of the week.

$$
\begin{aligned}
Returns_{it} = {} & \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Monday_t + \boldsymbol{\beta_2} Friday_t + \boldsymbol{\beta_3} Earnings_{it} + \boldsymbol{\beta_4} Beta_{it} + \boldsymbol{\beta_5} ROA_{it} \\
& + \boldsymbol{\beta_6} Age_{it} + \boldsymbol{\beta_7} MaxReturn_{it} + \boldsymbol{\beta_8} LnPrice_{it} + \boldsymbol{\beta_9} LnSize_{it} \\
& + \boldsymbol{\beta_{10}} Illiquidity_{it} + \boldsymbol{\beta_{11}} 52WeekHigh_{it} +
\end{aligned}
$$

$$
\begin{aligned}
\boldsymbol{\beta_{12}} & Monday_t * Earnings_{it} + \boldsymbol{\beta_{13}} Monday_t * Beta_{it} + \boldsymbol{\beta_{14}} Monday_t * ROA_{it} \\
& + \boldsymbol{\beta_{15}} Monday_t * Age_{it} + \boldsymbol{\beta_{16}} Monday_t * MaxReturn_{it} \\
& + \boldsymbol{\beta_{17}} Monday_t * LnPrice_{it} \\
& + \boldsymbol{\beta_{18}} Monday_t * LnSize_{it} + \boldsymbol{\beta_{19}} Monday_t * Illiquidity_{it} \\
& + \boldsymbol{\beta_{20}} Monday_t * 52WeekHigh_{it} +
\end{aligned}
$$

$$
\begin{aligned}
\boldsymbol{\beta_{21}} & Friday_t + \boldsymbol{\beta_{22}} Friday_t * Earnings_{it} + \boldsymbol{\beta_{23}} Friday_t * Beta_{it} + \boldsymbol{\beta_{24}} Friday_t * ROA_{it} \\
& + \boldsymbol{\beta_{25}} Friday_t * Age_{it} + \boldsymbol{\beta_{26}} Friday_t * MaxReturn_{it} + \boldsymbol{\beta_{27}} Friday_t \\
& * LnPrice_{it} + \boldsymbol{\beta_{28}} Friday_t * LnSize_{it} + \boldsymbol{\beta_{29}} Friday_t * Illiquidity_{it} \\
& + \boldsymbol{\beta_{30}} Friday_t * 52WeekHigh_{it} + V_{it}
\end{aligned}
$$

The coefficients $\boldsymbol{\beta_{12}}$ to $\boldsymbol{\beta_{20}}$ are interaction terms between the Monday variable, where Monday = 1, and the firm characteristics. These coefficients are therefore interpreted as the effect of a change in each firm characteristic on returns on Mondays, relative to the other days. The equivalent applies to the coefficients $\boldsymbol{\beta_{21}}$ to $\boldsymbol{\beta_{30}}$, which are interaction terms between the Friday variable and the firm characteristics. The coefficients $\boldsymbol{\beta_3}$ to $\boldsymbol{\beta_{11}}$ are the effects of the firm characteristics in the remaining weekdays. For each characteristic in which sentiment sensitivity is increasing (*Beta, Max Return, Illiquidity* and *52 Week High*), we would expect the interaction terms with Monday to be negative, indicating that these traits affect Monday returns negatively relative to the other days, and vice versa for Friday. The opposite is the case for each characteristic in which sentiment sensitivity is decreasing (*Earnings, ROA, Age, Price* and *Size*).

We argue that price and size should both be logarithmic, as the effect on returns of positive or negative information may have a much greater impact on low priced and small stocks than stocks with medium price and size. The effect of such information on medium price and size stocks may only be moderately larger than for large price and size stocks. A Davidson-

MacKinnon test indicates that log-transformed values of these variables provide a better goodness-of-fit[9].

4.1.3 Equation 4 – The Settlement Time Hypothesis

In testing whether the settlement procedures in the Norwegian stock markets contribute to higher Friday and lower Monday returns, a change in the settlement time from *T+3* to *T+2* in October 2014 (Oslo Børs, 2013) is utilized. We test whether daily returns on Mondays and Fridays are affected differently than returns on the other days of the week. Consequently, we first propose the following equation.

$$Returns_{it} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Monday_t + \boldsymbol{\beta_2} SettlementChange_t + \boldsymbol{\beta_3} Monday_t * SettlementChange_t + \boldsymbol{\beta_4} Friday_t + \boldsymbol{\beta_5} Friday_t * SettlementChange_t + V_{it}$$

The change in settlement time decreases the amount of settlement days from five to four for Friday transactions, thus decreasing the cost of foregone interest. We therefore test whether Friday returns, $\boldsymbol{\beta_5}$, decrease more, relative to the other days. Further, we also test whether Monday returns, $\boldsymbol{\beta_3}$, increase more because of the change than the other days**.**

However, note that the reduction in settlement time for transactions done on Tuesdays is the same as for Mondays. Similarly, the reduction in settlement time for transactions on Thursdays is the same as for Fridays. Wednesday transactions, however, experienced a reduction in settlement time from five days before October 2014, to two days after. The main effect of the change in settlement time on Tuesday-, Wednesday- and Thursday returns in the equation above ($\boldsymbol{\beta_2}$), does therefore not have a clear prediction. Comparing the effect, of the change on Mondays and Fridays to the other days of the week, may therefore not give cause to conclude

[9] The Davidson-MacKinnon test can be seen in section 8.1 in the appendix.

whether the effect of settlement time influences the higher Friday, and lower Monday returns. We therefore further reparametrize the equation, to identify the main effect of the change in settlement time on Fridays and Mondays respectively. We argue that if longer settlement periods for Friday transactions than Monday transactions drives Friday returns up, and Monday returns down – thus contributing to the Day-of-the-Week effect – the settlement time reduction in 2014 should cause Friday returns to decrease, and Monday returns to increase.

4.1.4 Equation 5 – The Speculative Short Interest Hypothesis

To test the *speculative short interest hypothesis*, we examine whether the effect of speculative short interest on returns is different on Fridays and Mondays, relative to the other days of the week. Furthermore, we wish to test whether firms with high speculative short interest exhibit higher Friday and lower Monday returns than firms with low speculative short interest. As discussed previously, stocks with actively traded put options should exhibit lower Day-of-the-Week effects, thus exhibiting lower Friday and higher Monday returns, all else equal. Thus, we propose the following equation.

$$Returns_{it} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Monday_t + \boldsymbol{\beta_2} Friday_t + \boldsymbol{\beta_3} PutsDummy_{it} + \boldsymbol{\beta_4} Monday * PutsDummy_{it} + \boldsymbol{\beta_5} Friday_t * PutsDummy_{it} + V_{it}$$

The *speculative short interest hypothesis* suggests that $\boldsymbol{\beta_4}$ should be positive, meaning that the effect on returns of a stock having actively traded put options is higher on Mondays relative to the other days of the week. Further, $\boldsymbol{\beta_5}$ should be negative, meaning that the effect of a stock having actively traded put options, on returns, is lower on Fridays relative to the other days of the week.

4.1.5 Equation 6 – Comparison

After testing the hypothesized explanations for the anomaly, we want to compare the effects in unison. As mentioned in the theoretical framework, an equation that includes the variables from the *speculative short interest*, *sentiment* and *settlement time* hypotheses allows us to examine which of the effects are the most prominent and whether there is a degree of omitted variable bias in any of the individual equations. Equation 6 is therefore a combined equation of equations 2, 4 and 5.

$$\begin{aligned} Returns_{it} = {} & \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Monday_t + \boldsymbol{\beta_2} Friday_t + \boldsymbol{\beta_3} PutsDummy_{it} \\ & + \boldsymbol{\beta_4} SentimentScore_{it} + \boldsymbol{\beta_5} SettlementChange_t \\ & + \boldsymbol{\beta_6} Monday_t * PutsDummy_{it} + \boldsymbol{\beta_7} Friday_t * PutsDummy_{it} \\ & + \boldsymbol{\beta_8} Monday_t * SentimentScore_{it} + \boldsymbol{\beta_9} Friday_t * SentimentScore_{it} \\ & + \boldsymbol{\beta_{10}} Monday_t * SettlementChange_t + \boldsymbol{\beta_{11}} Friday_t \\ & * SettlementChange_t + V_{it} \end{aligned}$$

4.2 Estimation models

There are several types of estimation methods that are suitable for dealing with panel data. In the following, we discuss the use of pooled OLS and Fixed Effects (FE) estimators. The simplest method to use is pooled OLS. This method ignores the panel structure of the data and simply pools it together. Thus, finding the single linear regression line that gives the least squared error. A weakness of pooled OLS is that it does not distinguish between time dependent errors v_t, unobserved heterogeneity a_i and idiosyncratic errors u_{it}. This creates a composite error term, $v_{it} = v_t + a_i + u_{it}$. Having a composite error term means that, when using pooled OLS, there is no way of isolating the unobserved heterogeneity a_i. A Fixed Effect estimator, conversely, provides us with a way of dealing with this. In this estimation method, the time invariant unobserved heterogeneity is removed by time demeaning. This process removes the within i time averages for all variables in the model. By doing so it removes the time invariant unobserved heterogeneity, but also all other time fixed effects.

Wooldridge (2018) argues that Fixed Effect estimators are the preferred estimation method when working with unbalanced panels, such as ours. To control for unobserved heterogeneity, we use the Fixed Effects estimation method combined with pooled OLS. If the unobserved heterogeneity is correlated with the explanatory variables, the results will differ between the two methods. This can indicate a bias in the pooled OLS estimation. Because of this, it is useful to present the results both from the pooled OLS and Fixed Effects estimations.

4.2.1 Assumptions

We start by looking at the Gauss Markov assumptions for OLS and Fixed Effects estimators, as defined by Wooldridge (2018). These assumptions ensure that an estimator is consistent and unbiased, a state that can be described with the acronym, BLUE[10]. The full assumptions state that an estimator should be linear in parameters, randomly sampled, that there is no perfect collinearity, that the conditional mean is zero, that the residuals are homoscedastic and that there is no autocorrelation. As linearity in parameters and random sampling have partially been discussed in the previous sections, the relevant assumptions to discuss in further detail are those of no perfect collinearity, zero conditional mean, homoscedasticity and autocorrelation. In the following, we discuss to what degree they are fulfilled in our estimations and which steps are taken to address any issues.

We start by examining the assumption of no perfect collinearity. This is not a problem in the estimations, as none of the explanatory variables are perfectly collinear. It is not unlikely, however, that some of the variables are highly correlated. Some correlation between the variables is to be expected, but with too much correlation the issue of multicollinearity can arise (Wooldridge, 2018). This can lead to inflated variance values which artificially reduce the power of the coefficients. A method for resolving this is to remove one or more of the highly correlated variables (James, et al., 2017). To investigate whether multicollinearity is an issue in the estimations, we perform Variance Inflation Factor (VIF) tests[11]. A VIF score

[10] BLUE is an abbreviation for Best Linear Unbiased Estimator and is an acronym given to estimation models that adhere to the Gauss Markov assumptions (Wooldridge, 2018).

[11] A Variance Inflation Factor test measures the variance of a specific variable when fitted in the full estimation relative to when fitted individually (James, et al., 2017). This measures multicollinearity against all other variables.

shows how much the variance is inflated due to multicollinearity with all other predictive variables. James, et al. (2017) recommends further investigating variables with a VIF value above 5, as these may start to be problematic, although the cutoff is not exact and there is no universal agreed upon limit in academia. Allison (2012) is stricter and suggests a limit of 2.5. All the estimations have VIF values below 5 for their respective predictive variables, except for equations 2, 3 and 6[12], where there are high VIF values for the *Monday* and *Friday* variables and their interaction terms. This is to be expected when including the product of two variables, as this naturally inflates the VIF score and is not a problem[13]. In estimation 3, however, we observe that *LnSize* and *LnPrice* have VIF values close to 5, indicating that they may be overly correlated with the other predictive variables. The correlation matrix suggests that most of this correlation is between the pair, as they are highly correlated directly with each other[14].

To investigate if further action is necessary, we estimate the model with both variables, as well as without *LnSize* and *LnPrice* respectively[15]. When estimating the model without *LnSize,* it yields similar results as when it is estimated with both variables. However, when *LnPrice* is removed, this does not increase the power of *LnSize* interacted with Mondays or Fridays, as the correlation between *LnSize* and *LnPrice* might suggest. This indicates that most of the explanatory power is captured by *LnPrice*, and the high VIF value for *LnSize* suggests that it is correlated with the other variables, to a higher degree, than *LnPrice*. This effect is visible in the correlation matrix as well. When deciding whether to remove variables, there is always a tradeoff between omitted variable bias and multicollinearity. The effect of multicollinearity in estimation 3 can be reduced by removing *LnSize* but by doing so, this also slightly increases the omitted variable bias. The problem of multicollinearity is decided to be more important in

---

[12] See appendix part 8.4 for the Variance Inflation Factor tests.

[13] This is not a problem because the p-values are not affected when including products of variables (Allison, 2012).

[14] *LnSize* and *LnPrice* have a correlation value of 0.717, which can be seen in the appendix part 8.5.

[15] See appendix 8.6 for the estimated models.

this context, as the individual power of *LnSize* is small. Based on the evaluations mentioned, we choose to remove *LnSize* to reduce multicollinearity in estimation 3.

Next, we turn to the assumption of zero-conditional mean, which states that all the independent variables should be uncorrelated with the error term. If an independent variable is correlated with the error term, OLS attributes parts of the error variance to the independent variable. Violating the zero conditional-mean assumption may therefore bias the coefficient estimates, which creates an endogeneity problem. To explore whether we have a problem with endogeneity, we create residual plots for all the estimations[16]. These plots do not show strong discernable patterns to indicate endogeneity. Endogeneity problems are typically caused by omitted variable bias, measurement errors or simultaneity (Wooldridge, 2018). We assume that our rebalancing intervals are appropriate and that there are no large measurement errors in the data we are using. Regarding omitted variable bias and simultaneity, returns can be influenced by many factors. We cannot completely rule out that there is a degree of simultaneity for some of the predictive variables. However, simultaneity is unlikely to have a large effect. This is because the dependent variable in question, daily return, is unlikely to strongly influence the independent variables, which have a much larger time span. It is not possible to rule out omitted variable bias either, but using Fixed Effects estimators should reduce the likelihood of it in our estimations, as this excludes time-invariant variables (Wooldridge, 2018). In summary, the assumption is of exogeneity is assumed to hold for all equations.

Further, Wald and Breusch Pagan tests are conducted to investigate the assumptions of homoscedasticity[17]. The tests show a clear presence of heteroscedasticity in all the equations, indicating that the variance of the residuals is not constant. There is also a problem with

[16] See appendix part 8.7 for the residual plots.

[17] See the appendix part 8.2 for the Wald and Breusch Pagan tests

correlation between the residuals, as the Wooldridge test indicates autocorrelation in estimations 1, 2, 3 and 6[18]. To adjust for both issues, standard errors are clustered by company in all estimations.

The corrections done to the estimations should ensure that the estimations are unbiased and consistent. There is, however, an additional assumption we will consider, namely that of stationarity. The presence of a unit root or trend can cause a time series to exhibit non-stationarity. Because we are using relative daily returns, this is unlikely to be a problem with the data. To further investigate this, we also perform an Augmented Dickey-Fuller test on daily returns, which indicates stationarity[19].

4.2.2 Time and Group Fixed Effects

When dealing with panel data, it is important to consider if any fixed effects may be influencing the estimations (Wooldridge, 2018). These can be incorporated into the model, as to not bias the estimated coefficients. The base Fixed Effects estimation model uses unit (company) fixed effects to remove all between-unit variation. In the following, we discuss the relevance of both time (year) and group (industry) fixed effects.

Time fixed effects, with yearly dummies, capture the influence of time series trends. This effect can be important when examining absolute stock prices over time, as they will naturally increase due to economic growth. Thus, controlling for time fixed effects may influence the results. We explore the matter by running the estimation models with and without time fixed

[18] See the appendix part 8.3 for the Wooldridge tests

[19] See the appendix part 8.9 for the Augmented Dickey-Fuller test

effects[20]. As the results are very similar, we will not control for time fixed effects, as the omitted variable bias of leaving them out is likely small.

Industry fixed effects can only be added to the pooled OLS regression, as they are time invariant. If any of the industries have a major influence on returns, including industry fixed effects could be relevant. Adding industry dummies to the pooled OLS estimations do not, however, affect the results to a large extent[21] and are therefore not included. It is also worth noting that when including industry or time dummies, the Pooled OLS estimation is technically a Fixed Effect estimation. In the appendix, these are still referred to as Pooled OLS for simplicity.

[20] See appendix part 8.8 for the equations with time fixed effects.

[21] See appendix 8.8 for the equations with group fixed effects.

5. Main Findings

In this section, the main findings of the thesis are presented. This starts with equation 1 and a discussion of the Day-of-the-Week effect in Norway. The results indicate that daily returns are higher on Fridays and lower on Mondays relative to the other days of the week. After which, the focus turns to the hypothesized driving forces of the effect; *the sentiment-*, *the settlement time-* and *the short interest hypothesis*.

5.1 The Day-of-the-Week Effect

As discussed previously, the first equations goal is to test hypothesis one. More specifically, whether daily returns are lower on Mondays and higher on Fridays relative the other days of the week.

Table 5-1 - The Day-of-the-Week Effect

In this table, equation 1 is presented with Fixed Effect and pooled OLS estimators. Monday and Friday represent dummy variables with a value of 1 if the day is respectively Monday or Friday, and zero otherwise. Standard errors are clustered by company in both estimations, and robust standard errors are presented in parentheses. The following model is estimated.

$$\text{Returns}_{it} = \beta_0 + \beta_1 \text{Monday}_t + \beta_2 \text{Friday}_t + V_{it}$$

	(1) Fixed Effect Returns	(2) Pooled OLS Returns
Monday	**-0.05921****	**-0.06005****
	(0.02383)	(0.02456)
Friday	**0.23309*****	**0.23270*****
	(0.02218)	(0.02210)
_cons	0.04933***	0.04957**
	(0.00761)	(0.01988)
Obs.	553181	553181
Adj. R-squared	0.00019	0.00019

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

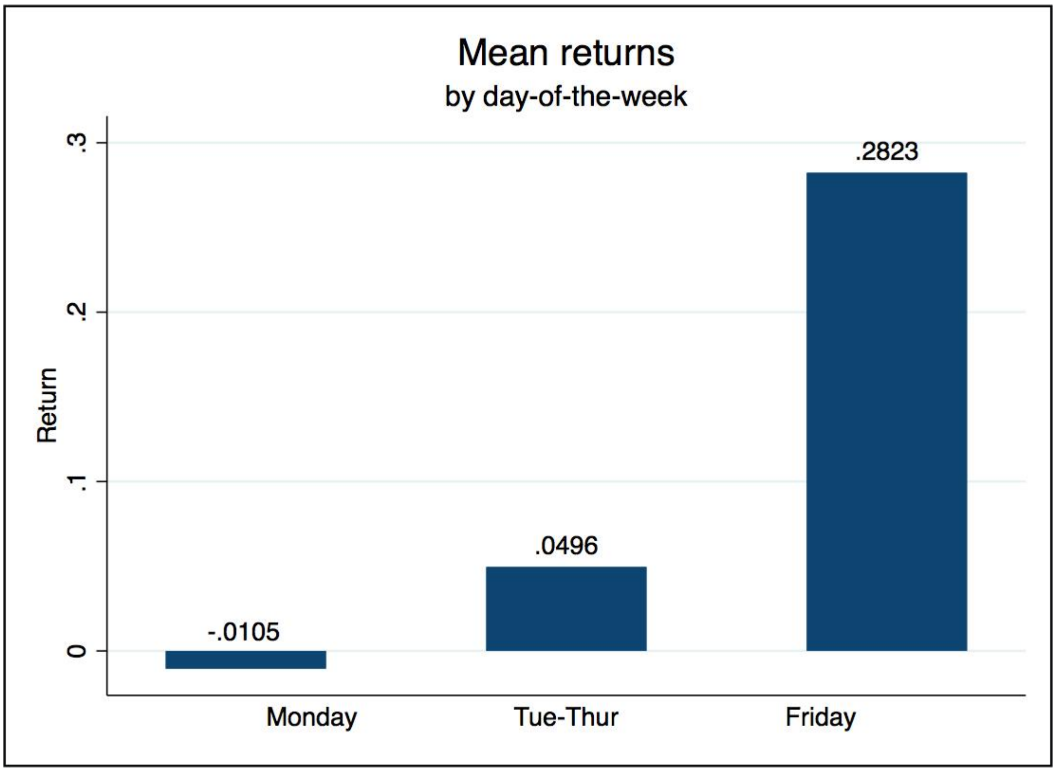
The coefficients *Monday* and *Friday* represent binary variables equal to one if the day is Monday or Friday respectively, and zero otherwise. Thus, they represent the marginal effect of the day being Monday and Friday on daily returns. The *Monday* coefficient is interpreted as the average daily return on Mondays relative to the other days of the week, and similarly for the *Friday* coefficient. The constant indicates the mean daily return for Tuesdays through Thursdays, which is 0.05%. The mean daily return for all days is 0.085%.

The results indicate that the effect of the day being Monday and Friday is statistically significant at the 5%-level. Mondays are associated with lower-than-average daily returns and Fridays are associated with higher-than-average daily returns. Daily returns on Mondays are 0.059 percentage points lower than the other days of the week, whereas daily Friday returns are 0.23 points higher compared to the rest of the week. The effect of the day being Monday and Friday respectively, on daily returns, is therefore equivalent to a factor of 0.7 (Mondays) and 2.7 (Fridays) of the mean daily return for all days. These results are in favor of a DOW-effect in the Norwegian securities market, in which prices increase from Thursday close to Friday close, and decrease from Friday close to Monday close. Average Monday and Friday returns, as well as the average return on Tuesdays, Wednesdays and Thursdays are presented in figure 5-1.

The mean daily Monday return is -0.011%, the mean Friday return is 0.28%, while the average return for Tuesdays through Thursdays is 0.05%. This indicates an average Weekend Effect of 0.29%. At the 5%-level of significance it can be rejected that both the mean Monday and the mean Friday returns are equal to the mean returns on Tuesdays through Thursdays.

Figure 5-1 - Mean Returns by Day of the Week

In this figure, the daily mean returns by Day-of-the-Week are presented for Mondays, Fridays and Tuesdays through Thursdays.



5.2 Sentiment Hypothesis

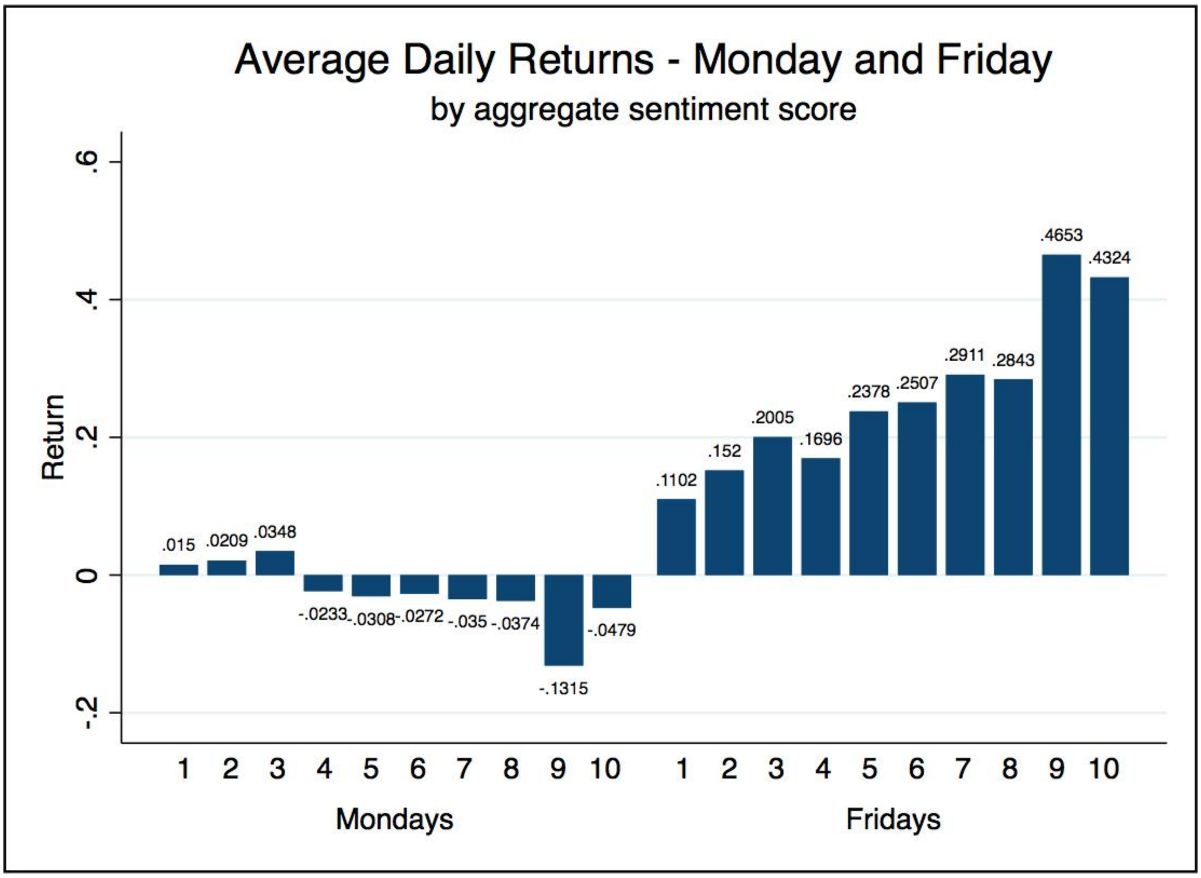
This section focuses on the *sentiment hypothesis*. The hypothesis suggests that the observed Day-of-the-Week effect in equation 1 is caused by changes in investor sentiment, in which sentiment increases from Thursday to Friday, and decreases from Friday to Monday. To test for the effect of investor sentiment, we examine whether the sentiment characteristics of firms affect daily returns on Monday and Friday differently than the other days of the week. First the results from equation 2, in which the aggregate sentiment score proxies for the sentiment sensitivities of firms, is presented and discussed. Following this, is a discussion of the results of equation 3, in which each sentiment trait is included separately.

5.2.1 Aggregate Sentiment Score

In equation 2, we generate an aggregate measure of sensitivity to changes in investor sentiment. This is based on the nine identified firm specific traits from section three. Each firm specific trait is divided into deciles for each month and given a score between 1 and 10 based on its sensitivity to changes in investor sentiment (1 = *low* sensitivity to changes in investor sentiment, 10 = *high* sensitivity to changes in investor sentiment). To illustrate this, figure 5-2 graphs the mean Monday and Friday returns for each decile of the aggregate sentiment score. This displays the relationship between sentiment sensitivity and daily returns on these days.

Figure 5-2 - Mean Monday and Friday Returns by Aggregate Sentiment Score

In this figure the mean Friday and Monday returns are illustrated by their sentiment sensitivity. A sentiment sensitivity of 1 corresponds to firms with an aggregate sentiment score of <10th percentile by month (Low sensitivity to changes in sentiment). A sentiment sensitivity of 10 corresponds to firms with an aggregate sentiment score of >90th percentile by month (high sensitivity to changes in sentiment).



We observe that the Monday returns *seem* to be decreasing with an increase in aggregate sentiment, while Friday returns *seem* to be positively correlated with the aggregate sentiment score. The average daily Monday return for stocks with an aggregate sentiment score below the 10th percentile is 0.015%, while it is -0.048% for stocks with an aggregate sentiment above the 90th percentile. However, we fail to reject that the mean Monday return for stocks with an aggregate sentiment below the 10th percentile is equal to the mean return for stocks with an aggregate sentiment above the 90th percentile.

The average daily Friday return for stocks with an aggregate sentiment score below the 10th percentile is 0.11%, while for stocks with an aggregate sentiment score above the 90th, it is 0.43%. It can be rejected at the 1%-level of significance that these mean returns are equal. This indicates that Friday returns, for stocks with a high sensitivity to sentiment changes, are higher than for stocks with a low sensitivity to sentiment changes. This is consistent with the sentiment hypothesis.

Further, we present the results for equation 2 and its six sub-equations. In testing the sentiment hypothesis, the aim is to explore whether the effect of sentiment sensitivity on daily returns is different on Mondays and Fridays, relative to the other days of the week. Monday and Friday are therefore interacted with the aggregate sentiment score (sub-equation 1 and 2). Further, an examination of the main effect of sentiment sensitivity on Friday returns (sub-equations 3 and 4) and Monday returns (sub-equations 5 and 6), respectively, are presented.

The *Friday*SentimentScore* coefficient in sub-equations 1 and 2 is statistically significant at the 1%-level. This indicates that the slope of the sentiment score coefficient is different on Fridays, relative to the other days of the week. In other words; daily return on Fridays are more sensitive to a change in the aggregate sentiment score than the other days of the week. The *SentimentScore* variable, which in this case represents the general effect of aggregate sentiment on returns on Tuesdays through Thursdays, cannot be concluded to be significantly different from zero. The fact that Friday returns exhibit an increased sensitivity to changes in the sentiment sensitivity of stocks, is in line with the sentiment hypothesis. However, there is no evidence to conclude that Monday returns similarly exhibit increased sensitivity to changes in sentiment sensitivity.

Table 5-2 - Aggregate Sentiment Score

In this table, equation 2 is presented with Fixed Effect and pooled OLS estimators. Each firm is, for each month, given a score between 1 and 10 for each individual sentiment trait. This is based on deciles, in which 1 = low sensitivity to sentiment change and 10 = high sensitivity to sentiment change. SentimentScore is the average sentiment score for all available sentiment traits, for a given company, in each month. The following model is estimated.

$$\text{Returns}_{it} = \beta_0 + \beta_1\text{Monday}_t + \beta_2\text{SentimentScore}_{it} + \beta_3\text{Monday}_t * \text{SentimentScore}_{it} + \beta_4\text{Friday}_t + \beta_5\text{Friday}_t * \text{SentimentScore}_{it} + V_{it}$$

We further reparametrize to identify the main effect of sentiment score on Fridays (sub-equations 3 and 4), and on Mondays (sub-equations 5 and 6). Standard errors are clustered by company, and robust standard errors are presented in parentheses. With an alpha of 5%, statistically significant coefficients are highlighted.

	(1) Fixed Effect ***- All days*** Returns	(2) Pooled OLS ***- All days*** Returns	(3) Fixed Effect ***- Fridays*** Returns	(4) Pooled OLS ***- Fridays*** Returns	(5) Fixed Effect ***- Mondays*** Returns	(6) Pooled OLS ***- Mondays*** Returns
Monday	0.05357	0.05357				
	(0.08188)	(0.08180)				
SentimentScore	0.03274	-0.00115	**0.06758*** **	**0.06380*** **	-0.00983	-0.02146**
	(0.03060)	(0.01277)	**(0.01936)**	**(0.01048)**	(0.01723)	(0.01084)
Mon*SentimentScore	-0.02036	-0.02031				
	(0.01794)	(0.01793)				
Friday	-0.11008	-0.10977				
	(0.07364)	(0.07372)				
Fri*SentimentScore	**0.06503*** **	**0.06496*** **				
	(0.01621)	**(0.01623)**				
_cons	-0.14718	0.03355	-0.09635	-0.07621	0.02504	0.08713*
	(0.15920)	(0.05673)	(0.10328)	(0.04756)	(0.09194)	(0.04906)
Obs.	400273	400273	80049	80049	78685	78685
Adj. R-squared	0.00038	0.00034	0.00023	0.00078	0.00000	0.00007

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Further, the sentiment hypothesis states that sentiment *sensitive* stocks should exhibit higher Friday and lower Monday returns than sentiment *insensitive* stocks. We observe that the *SentimentScore* coefficient is statistically significant at the 1%-level in sub-equation 3 and 4. The Fixed Effect coefficient indicates that an increase in the aggregate sentiment score of 1, is associated with an increase in Friday returns of 0.068 percentage points; in other words, sentiment *sensitive* stocks exhibit higher Friday returns than sentiment *insensitive* stocks. All else equal, a highly sentiment sensitive stock with a sentiment score of 10, yields 0.61

percentage points higher daily Friday returns than a stock with a sentiment score of 1. The effect on Friday returns of an increase in the sentiment score of 1, is equivalent to a factor of 0.8 of the mean daily return for all days. This is consistent with the sentiment hypothesis. Observe that, in sub-equations 5 and 6, the results from the pooled OLS and Fixed Effects estimations are substantially different. Thus, we should be careful in interpreting the significance of sentiment sensitivity on Monday returns, as the pooled OLS estimation may be biased.

In summary, we show that the effect of firm sentiment sensitivity on daily returns on Fridays is different than the other days of the week, and that sentiment sensitive firms exhibit higher Friday returns than sentiment insensitive firms. Both these findings are consistent with the sentiment hypothesis. The evidence suggests that the observed higher Friday returns may in part be driven by a change in investor sentiment from Thursday to Friday. However, we cannot conclude that decreased investor sentiment from Friday to Monday explains parts of the observed lower Monday returns.

5.2.2 Firm Characteristics in Sentiment Effect

As previously discussed, the aim of equation 3 is to explore which of the firm characteristics may drive the increased sensitivity to changes in investor sentiment, and therefore the Day-of-the-Week effect. Therefore, we examine which of the sentiment traits (*Beta, ROA, Earnings, Price, Size, Age, Max Return, Illiquidity and 52-week high*) affect daily returns differently on Mondays and Fridays, relative to the other days of the week. Note that *LnSize* is not included in the equation 3, as per the discussion in part four.

Table 5-3 - Sentiment Traits

In this table, equation 3 is presented with both pooled OLS and Fixed Effect estimators. Standard errors are clustered by company in both estimations. Robust standard errors are presented in parentheses. With an alpha of 5%, statistically significant coefficients are highlighted. The following model is estimated.

$$Returns_{it} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1} Monday_t + \boldsymbol{\beta_2} Friday_t + \boldsymbol{\beta_3} Earnings_{it} + \boldsymbol{\beta_4} Beta_{it} + \boldsymbol{\beta_5} ROA_{it} + \boldsymbol{\beta_6} Age_{it} + \boldsymbol{\beta_7} MaxReturn_{it} + \boldsymbol{\beta_8} LnPrice_{it} + \boldsymbol{\beta_9} LnSize_{it} + \boldsymbol{\beta_{10}} Illiquidity_{it} + \boldsymbol{\beta_{11}} 52WeekHigh_{it} + \boldsymbol{\beta_{12}} Monday_t * Earnings_{it} + \boldsymbol{\beta_{13}} Monday_t * Beta_{it} + \boldsymbol{\beta_{14}} Monday_t * ROA_{it} + \boldsymbol{\beta_{15}} Monday_t * Age_{it} + \boldsymbol{\beta_{16}} Monday_t * MaxReturn_{it} + \boldsymbol{\beta_{17}} Monday_t * LnPrice_{it} + \boldsymbol{\beta_{18}} Monday_t * LnSize_{it} + \boldsymbol{\beta_{19}} Monday_t * Illiquidity_{it} + \boldsymbol{\beta_{20}} Monday_t * 52WeekHigh_{it} + \boldsymbol{\beta_{21}} Friday_t + \boldsymbol{\beta_{22}} Friday_t * Earnings_{it} + \boldsymbol{\beta_{23}} Friday_t * Beta_{it} + \boldsymbol{\beta_{24}} Friday_t * ROA_{it} + \boldsymbol{\beta_{25}} Friday_t * Age_{it} + \boldsymbol{\beta_{26}} Friday_t * MaxReturn_{it} + \boldsymbol{\beta_{27}} Friday_t * LnPrice_{it} + \boldsymbol{\beta_{28}} Friday_t * LnSize_{it} + \boldsymbol{\beta_{29}} Friday_t * Illiquidity_{it} + \boldsymbol{\beta_{30}} Friday_t * 52WeekHigh_{it} + V_{it}$$

	(1) Fixed Effect Returns	(2) Pooled OLS Returns
Monday	-0.08548	-0.08279
	(0.06045)	(0.06047)
Earnings	0.02882	0.06252***
	(0.02765)	(0.02170)
Beta	-0.04386**	-0.03904**
	(0.02211)	(0.01783)
ROA	0.66621**	0.50087**
	(0.25921)	(0.19727)
LnPrice	-0.10463***	-0.03941***
	(0.01682)	(0.00755)
Age	-0.00566**	0.00179
	(0.00267)	(0.00132)
MaxReturn	-0.10620	-0.06345
	(0.08067)	(0.07125)
Illiquidity	21.88128	25.20259
	(45.05213)	(46.65077)
52WeekHigh	0.02031**	0.01438
	(0.00945)	(0.01012)
Monday*Earnings	-0.02457	-0.02548
	(0.04823)	(0.04829)
Monday*Beta	-0.01753	-0.01875
	(0.03289)	(0.03307)
Monday*ROA	0.34023	0.34105
	(0.49662)	(0.49754)
Monday*LnPrice	**0.03449****	**0.03442****
	(0.01349)	(0.01350)
Monday*Age	-0.00257	-0.00257
	(0.00158)	(0.00159)
Monday*MaxReturn	0.11284	0.10714
	(0.09466)	(0.09168)
Monday*Illiquidity	-31.97048	-31.77012
	(83.76265)	(84.04999)
Monday*52WeekHigh	-0.00910	-0.00933
	(0.01603)	(0.01607)
Friday	0.39256***	0.39100***
	(0.06016)	(0.06023)
Friday*Earnings	**-0.10026****	**-0.09929****
	(0.04309)	(0.04318)
Friday*Beta	0.01577	0.01554
	(0.03848)	(0.03859)
Friday*ROA	-0.30730	-0.30657
	(0.37924)	(0.37892)
Friday*LnPrice	**-0.02994****	**-0.02983****
	(0.01337)	(0.01336)
Friday*Age	**-0.00279***	**-0.00279***
	(0.00156)	(0.00156)
Friday*MaxReturn	0.07623	0.07800
	(0.11693)	(0.11804)
Friday*Illiquidity	101.56278	100.26629
	(144.42360)	(143.91222)
Friday*52WeekHigh	0.00142	0.00161
	(0.01279)	(0.01274)
_cons	0.38988***	0.09506***
	(0.05493)	(0.02634)
Obs.	400273	400273
Adj. R-squared	0.00065	0.00046

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

We observe that *Monday*LnPrice* is statistically significant at the 5%-level of significance, with a coefficient of 0.034 in both sub-equations. This indicates that price has a different effect on daily returns on Mondays relative to the other days. This further means that an increase in the stock price of one percent is associated with a 0.00034 percentage points higher increase in daily returns on Mondays, relative to the other days of the week[22]. The same, but opposite, effect applies to *Friday*LnPrice*, which has a statistically significant negative coefficient of -0.030 in both sub-equations. This indicates that an increase in size of one percent is associated with 0.0003 percentage points lower returns on Fridays, relative to the other days[23]. Furthermore, we find that *Friday*Earnings* is statistically significant the 5%-level of significance, with a coefficient of approximately -0.001. This means that having positive earnings is associated with a 0.001 percentage points lower return on Fridays, relative to the other days of the week. Lastly, we find that *Friday*Age* is negative and statistically significant at the 10%-level[24]. This indicates that a one-year decrease in age is associated with a 0.003 percentage point higher daily return on Friday, compared to the other days.

As previously discussed, the sentiment sensitivity of low-priced stocks arises from the fact that stocks with lottery-like properties have more speculative demand (Kumar, 2009). As sentiment decreases from Friday to Monday, the price of these low-priced stocks will be negatively affected, as the investors may place a lower estimation on positive *"lottery-outcomes"*. This may lead to the findings in equation 3. Namely that low prices of stocks affect returns negatively on Mondays, relative to the other days. When investor sentiment, in turn, increases from Thursday to Friday, the price of these lottery-like stocks is positively affected, as higher valuations are placed on positive *"lottery-outcomes"*.

---

[22] A one percent change in $\beta_{Monday*LnPrice}$ is associated with an exact unit change of $\beta_{Monday*LnPrice} \times \ln\left(\frac{101}{100}\right) =$ 0.0003383, which is equal to a percentage point increase of 0.0003383.

[23] A one percent change in $\beta_{Friday*LnPrice}$ is associated with an exact unit change of $\beta_{Friday*LnPrice} \times \ln\left(\frac{101}{100}\right) = 0.000299$, which is equal to a percentage point increase of 0.000299.

[24] *Friday*Age* has a p-value of 7.4%.

We further observe that Friday returns are negatively associated with earnings. This is consistent with, as discussed in section three, Baker & Wurgler's (2006) findings that unprofitable firms are harder to value and have more subjective valuations, making them more sensitive to changes in sentiment. The increased sentiment of investors from Thursday to Friday therefore cause their views on the prospects of these stocks to increase, which, in turn, increases Friday returns for these stocks.

In terms of the effect of *Age* on daily returns, we previously discussed that the sentiment sensitivity of young firms arises from the increased propensity to speculate in such stocks (Baker & Wurgler, 2006). As young stocks have less historical information to evaluate them by, investors may be more influenced by their current sentiment state in evaluating them (Clore et al. 1994). As sentiment increases on Fridays, the evaluations, and in turn prices of younger stocks therefore increase, leading to the observed *Friday*Age* coefficient in equation 3.

In summary, we have shown that earnings, price and age are the predominant sentiment traits. As such, the sentiment effects of these traits may explain why certain stocks exhibit higher Friday and lower Monday returns. We cannot conclude, however, that the mechanisms behind these results are driven by the sentiment sensitivity of such stocks, but the findings are, in large part, consistent with the sentiment hypothesis.

5.3 Settlement Time Hypothesis

Next, we turn to the settlement time hypothesis. As previously discussed, settlement time may affect returns on different days of the week differently and systematically. Since transactions are settled a given amount of business days after the transaction, the cost of carry for transactions done on different days is asymmetrical. To explore whether this influences the observed Day-of-the-Week effect, we take advantage of a change in settlement time in Norway in October 2014. Using this change, we can determine whether Monday and Friday returns are affected, and whether this effect is different for Mondays and Fridays relative to the other days.

On the 6th of October in 2014, Oslo Børs VPS reduced the settlement time from *T+3* to *T+2,* in accordance with CSD-directive (Oslo Børs, 2013). This natural experiment gives us the opportunity to study a variety of effects, such as whether sellers in fact require a higher price for a longer settlement time. For the purpose of our thesis, however, we are mainly interested in whether Monday and Friday returns changed as a result of the decreased settlement time, and if this change is significantly different for Mondays and Fridays relative to the other days of the week. If the observed higher Friday and lower Monday returns are caused, in part, by a difference in the "*forward premium*", a settlement time reduction from five to four days on Fridays should result in decreased daily Friday returns. The equation can be seen below.

Table 5-4 - Settlement Time

In this table, equation 4 is presented with both pooled OLS and Fixed Effect estimators. SettlementChange is a variable with a value of 0 for all days before October 6th, 2014, and 1 thereafter. In sub-equations 1 and 2, all days are included with separate interactions between Monday, Friday and SettlementChange. Further, we reparametrize to focus on the main effect of the change in settlement on Friday returns (sub-equations 3 and 4) and on Monday returns (sub-equations 5 and 6). All standard errors are clustered by company, and robust standard errors are presented in parentheses. The following model is estimated.

$$\text{Returns}_{it} = \beta_0 + \beta_1\text{Monday}_t + \beta_2\text{SettlementChange}_t + \beta_3\text{Monday}_t * \text{SettlementChange}_t + \beta_4\text{Friday}_t + \beta_4\text{Friday}_t * \text{SettlementChange}_t + V_{it}$$

	(1) Fixed Effect ***- All days***	(2) Pooled OLS ***- All days***	(3) Fixed Effect ***- Fridays***	(4) Pooled OLS ***- Fridays***	(5) Fixed Effect ***- Mondays***	(6) Pooled OLS ***- Mondays***
	Returns	Returns	Returns	Returns	Returns	Returns
Monday	-0.07238***	-0.07322***				
	(0.02768)	(0.02794)				
SettlementChange	-0.08318***	-0.00723	-0.02199	0.02172	-0.02240	0.03913
	(0.03213)	(0.02201)	(0.03863)	(0.04156)	(0.03699)	(0.03515)
Mon*SettlementChange	0.04665	0.04636				
	(0.03952)	(0.03970)				
Friday	0.22584***	0.22461***				
	(0.02841)	(0.02853)				
Fri*SettlementChange	0.02549	0.02895				
	(0.04268)	(0.04335)				
_cons	0.07274***	0.05160**	0.28841***	0.27622***	-0.00411	-0.02162
	(0.01483)	(0.02013)	(0.01077)	(0.01965)	(0.01053)	(0.01888)
Obs.	553181	553181	111179	111179	108261	108261
Adj. R-squared	0.00020	0.00018	0.00000	0.00000	0.00000	0.00000

Standard errors are in parenthesis

**** p<0.01, ** p<0.05, * p<0.1*

In sub-equations 1 and 2, we observe that neither the interaction term, *Monday*SettlementChange* or *Friday*SettlementChange*, yield statistically significant coefficients. This means that we do not have evidence to conclude that the change in settlement time in 2014 affected Monday and Friday returns differently than the other days of the week. Furthermore, we observe from sub-equations 3-6, that Friday and Monday returns did not change significantly after the change in settlement time from *T+3* to *T+2*. If the observed Monday and Friday effects from equation 1 are, in fact, partly explained by differences in settlement time, we would expect to see Monday returns increase and Friday returns decrease after the change.

The evidence therefore suggests that the difference in settlement days has little or no impact on Monday and Friday returns. It is therefore not likely to be a main driver of the Day-of-the-Week effect in the Norwegian securities markets.

5.4 Speculative Short Interest Hypothesis

We now turn to the *speculative short interest* hypothesis. As previously explained, Chen and Singal (2003) argue that speculative short sales affect price formation around the weekend; on Mondays and Fridays. As short position holders shy the premise of holding such positions outside trading days, they tend to buy back stocks on Fridays, and sell short on Mondays, causing both Friday demand and Monday supply to be systematically higher than on the other days. Stocks with actively traded put options should therefore have lower Friday, and higher Monday returns than the other days, as, all else equal, these stocks are likely to have less speculative short sales. To examine this, equation 5 is presented below.

Table 5-5 - Speculative Short Interest

In this table, equation 5 is presented with Fixed Effect and pooled OLS estimators, in which firms with actively traded put options are given a value of 1, and zero otherwise. Standard errors are clustered by company in both estimations, and robust standard errors are presented in parentheses. The following model is estimated.

$$\text{Returns}_{it} = \beta_0 + \beta_1\text{Monday}_t + \beta_2\text{Friday}_t + \beta_3\text{PutsDummy}_{it} + \beta_4\text{Monday} * \text{PutsDummy}_{it} + \beta_5\text{Friday}_t * \text{PutsDummy}_{it} + V_{it}$$

	(1) Fixed Effect Returns	(2) Pooled OLS Returns
Monday	-0.06279**	-0.06373**
	(0.02611)	(0.02692)
PutsDummy	-0.05208	-0.04924
	(0.03288)	(0.03099)
Monday*PutsDummy	0.03707	0.03807
	(0.03587)	(0.03649)
Friday	0.24671***	0.24627***
	(0.02406)	(0.02398)
Friday*PutsDummy	**-0.14767***	**-0.14746***
	(0.03818)	(0.03802)
_cons	0.05424***	0.05423**
	(0.00898)	(0.02184)
Obs.	552938	552938
Adj. R-squared	0.00019	0.00019

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Observe that *Monday*PutsDummy* is positive, and *Friday*PutsDummy* is negative, although only the latter is statistically significant. This indicates that stocks with actively traded put options exhibit lower Friday returns than the other days of the week. More specifically, the effect on returns, of the availability of actively traded put options, is 0.15 percentage points lower on Fridays compared to the other days. This is consistent with the hypothesis of speculative short sales, following the argument of Chen & Singal (2003). Speculative short positions, which are theorized to frequently be closed before the weekend and reopened after, contribute to driving Friday prices up, thus increasing returns. However, when investors can replace short sales with put options, they may prefer to do so. Therefore, all else equal, the availability of put options should be associated with lower daily returns on Fridays compared to the other days of the week, which is consistent with the findings in equation 5. The effect of put options on daily returns on Mondays, however, is not significantly different than the other days. Based on this, we are unable to conclude that speculative short sales influence the lower Monday returns from equation 1.

However, we argue that stocks with actively traded put options are likely also more liquid, larger and older. In other words, they may be less sensitive to changes in investor sentiment. Thus, the dummy for having actively traded put options and the aggregate sentiment score are likely negatively correlated. Consequently, the dummy coefficient for puts above, in equation 5, may be biased, as it may capture the effect of sensitivity to changes in investor sentiment, and not exclusively the effect of *less* speculative short sales. Next, we therefore test the effect of both speculative short sales and sentiment sensitivity simultaneously. This is to examine whether they may both explain the observed DOW-effect, or if one partly proxies for the other.

5.5 Comparative Equation

When having actively traded put options is negatively correlated with the sentiment score[25], equations 2 and 5 may not capture the true effect of sentiment sensitivity and speculative short interest, respectively, on Monday and Friday returns. The final equation, equation 6, therefore tests whether it is likely that both speculative short interest and sentiment sensitivity explain parts of the observed DOW-effect, or if one of the effects explain most of the observed return-pattern. The dummy for settlement change is also included, to control for any potential omitted variables with regards to this.

[25] The R-value equals -0.287, indicating that there is moderate correlation between PutsDummy and SentimentScore.

Table 5-6 - Speculative Short Interest, Sentiment Sensitivity and Settlement Change

In this table, equation 6 is presented. The following model is estimated with Fixed Effect and pooled OLS estimators. Standard errors are clustered by company in both estimations, and robust standard errors are presented in parentheses.

$$\begin{aligned}\mathrm{Returns}_{it} = {} & \beta_0 + \beta_1\mathrm{Monday}_t + \beta_2\mathrm{Friday}_t + \beta_3\mathrm{PutsDummy}_{it} + \beta_4\mathrm{SentimentScore}_{it} \\ & + \beta_5\mathrm{SettlementChange}_t + \beta_6\mathrm{Monday}_t * \mathrm{PutsDummy}_{it} + \beta_7\mathrm{Friday}y * \mathrm{Putsdummy}_{it} \\ & + \beta_8\mathrm{Monday}_t * \mathrm{SentimentScore}_{it} + \beta_9\mathrm{Friday}_t * \mathrm{SentimentScore}_{it} \\ & + \beta_{10}Monday_t * \mathrm{SettlementChange}_t + \beta_{11}\mathrm{Friday}_t * \mathrm{SettlementChange}_t + \mathrm{V}_{it}\end{aligned}$$

	(1) Fixed Effect Returns	(2) Pooled OLS Returns
Monday	0.04449	0.04421
	(0.08509)	(0.08504)
PutsDummy	-0.01759	-0.01398
	(0.04095)	(0.02643)
SettlementChange	-0.06852**	-0.03238
	(0.02994)	(0.02422)
SentimentScore	0.03429	-0.00183
	(0.03071)	(0.01340)
Monday*PutsDummy	-0.02283	-0.02265
	(0.03445)	(0.03451)
Monday*SettlementChange	0.05170	0.05207
	(0.03878)	(0.03875)
Monday*SentimentScore	-0.02157	-0.02149
	(0.01871)	(0.01869)
Friday	-0.09583	-0.09566
	(0.07814)	(0.07822)
Friday*PutsDummy	**-0.05413***	**-0.05442***
	(0.03051)	(0.03049)
Friday*SettlementChange	0.01503	0.01563
	(0.03964)	(0.03965)
Friday*SentimentScore	**0.06242*****	**0.06234*****
	(0.01687)	(0.01689)
_cons	-0.12999	0.04986
	(0.15591)	(0.05699)
Obs.	400030	400030
Adj. R-squared	0.00037	0.00033

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

We observe that both Friday interactions remain statistically significant at the 10%-level, indicating that both puts and sentiment sensitivity may affect returns differently on Fridays relative to the other days of the week. The coefficient *Friday*PutsDummy* is closer to zero in equation 6, indicating that it in equation 5 may have captured some of the sentiment effect. However, it seems that when controlling for sentiment sensitivity, the effect on returns of having actively traded puts is still lower on Fridays than on the other days of the week. This indicates that, given the assumption of speculative short sellers' preference for put options, the availability of such options reduces the effect of short positions on higher Friday demand, and therefore on the higher Friday returns. Furthermore, *Friday*SentimentScore* is still statistically significant at the 1%-level, and positive. This indicates that when controlling for puts, stocks with a high sensitivity to changes in investor sentiment still yield higher daily returns on Friday relative to the other days, consistent with the sentiment hypothesis. In terms of the negative Monday returns, however, it seems that the effect of neither puts or sentiment sensitivity is different on this day relative to the other days of the week. This indicates that we are not able to conclude that either of the hypotheses explain the negative Monday returns. The conclusion with regards to the change in settlement time remains unaltered, as we still observe that the effect on daily returns of this change is not statistically different on Mondays or Fridays, relative to the other days.

In conclusion, it seems that the higher Friday returns in the Day-of-the-Week effect in Norway may be partly explained by an increase in the sentiment of investors from Thursday to Friday. Further, speculative short sellers may contribute to the higher Friday returns, as closing such positions before the weekend cause higher demand, and in turn higher returns.

6. Conclusion

We study the Day-of-the-Week effect in the Norwegian securities market, and more precisely, whether returns on Fridays are higher, and returns on Mondays are lower, than the other days of the week. Using panel data for Norwegian public firms between 2000 and 2019, we find that there is evidence of the presence of a Day-of-the-Week effect in Norway, in which Monday returns are 0.059 percentage points lower than the other days of the week, and Friday returns are 0.23 percentage points higher than the other days of the week. Furthermore, we examine possible causes, in which we focus on the *sentiment-, short interest-* and *settlement time hypotheses*.

We identify nine firm characteristics that should render certain stocks more sensitive to such changes in investor sentiment. From these, we create an aggregate sentiment sensitivity score. The results indicate that stocks with a high sensitivity to changes in investor sentiment exhibit higher Friday returns than sentiment insensitive stocks. We also find that Friday returns are more sensitive to a change in such sentiment sensitivity, in which the effect of increased sentiment sensitivity on daily returns is higher on Fridays than the other days. This is consistent with the predictions of one of the behavioral explanations for the Day-of-the-Week effect; *the sentiment hypothesis*. We do not identify a similar, but opposite, effect for Monday returns. We can therefore not conclude that sentiment sensitive stocks exhibit lower Monday returns than sentiment insensitive stocks, or that the effect of sentiment sensitivity on returns is different on Mondays than the other days.

Speculative short sales may also contribute to the observed higher Friday return. The *speculative short sale hypothesis* states that speculative short sellers shy the premise of holding these risky positions when they are unable to trade over an extended period, like the weekend. As such, speculative short sellers may close their positions on Fridays, and reopen them on Mondays. This leads to higher demand on Fridays, and higher supply on Mondays, relative to the other days. Following Chen & Singal (2003), we use the availability of actively traded put options as a proxy for *less* of such speculative short sales. The results suggest that the effect of actively traded put options is associated with lower Friday returns than that of the other days. This indicates that as speculative short sellers can buy put options, rather than sell short, the positive effect on Friday returns of increased demand from the closing of short positions is reduced. However, we do not find similar but opposite results for Monday returns. We can consequently not conclude that the effect of put option availability on daily returns is different on Mondays than the other days.

The *settlement time hypothesis* suggests that as the settlement time, in calendar days, is longer for transactions done on some days than others, the higher cost of foregone interest increases daily returns for certain days. We find that a reduction in the settlement time from *T+3* to *T+2* in 2014, did not affect daily returns on Mondays or Fridays differently than the other days of the week. We further find that the reduction in settlement time was not associated with a change in Monday or Friday returns. Therefore, we argue that differences in settlement time do not contribute to the observed Day-of-the-Week effect.

In summary, the thesis establishes the presence of a Day-of-the-Week effect in the Norwegian securities market, in which the high Friday returns may be explained in part by the role of speculative short sales and changes in investor sentiment. However, we cannot conclude that there are no other related or unrelated explanations for the effect. The Day-of-the-Week effect is still partly an unexplained phenomenon, and further research is needed to establish the mechanisms causing Friday returns to be higher, and Monday returns to be lower than the other days of the week.

6.1 Limitations and Avenues for Further Research

The Day-of-the-Week effect is still, in large part, an unexplained phenomenon. As seen in this thesis, several hypotheses have been suggested, but the findings in the existing literature vary greatly. Therefore, much remains to be explored, especially for smaller markets, such as Norway. For further research on the anomaly in the Norwegian securities market, we propose examining longer time series of the major indices. By doing so, one can achieve a better understanding of the return generating process, as well as potential systematic differences in return variance. It would also be interesting to examine how the effect has evolved over time in the Norwegian securities market. Furthermore, examining intraday trading information in Norway could shed light on how the differences in daily returns are generated; whether open to close returns provide similar results as close to close.

In terms of a further examination of the causes of the effect, we especially point to the *speculative short interest hypothesis* as an avenue for further research. Using stock loan data, instead of the availability of put options as a proxy for speculative short interest may be interesting. In addition, there are several other theorized explanations, such as the timing of news releases, which could be of interest for further research.

7. References

Allison, P., 2012. *Statistical Horizons.* [Online]
Available at: https://statisticalhorizons.com/multicollinearity
[Accessed 1 June 2020].

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, January, 5(1), pp. 31-56.

Antoniou, C., Doukas, J. A. & Subrahmanyam, A., 2016. Investor Sentiment, Beta, and the Cost of Equity Capital. *Management Science*, 27 April, 62(2), pp. 347-367.

Apolinario, R. M. C., Apolinario, R. M. C. & Sales, L. J., 2006. Day of the Week Effect on European Stock Markets. *International Research Journal of Finance and Economics* , Issue 2, pp. 53-70.

Baker, M. & Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance*, August, 61(4), pp. 1645-1680.

Bali, T. G., Cakici, N. & Whitelaw, R. F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics*, February, 99(2), pp. 427-446.

Banz, R. W., 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics* , March, 9(1), pp. 3-18.

Birru, J., 2018. Day of the week and the cross-section of returns. *Journal of Financial Economics*, 24 June, 130(1), pp. 182-214.

Bodie, Z., Kane, A. & Marcus, A. J., 2018. *Investments.* New York: McGraw-Hill Education.

Chen, H. & Singal, V., 2003. Role of Speculative Short Sales in Price Formation: The Case of the Weekend Effect. *The Journal of Finance,* 21 March, 57(2), pp. 685-705.

Clare, A., Ibrahim, M. & Thomas, S., 1998. The Impact of Settlement Procedure on Day-of-the-Week Effects: Evidence from the Kuala Lumpur Stock Exchange. *Journal of Business Finance & Accounting*, May, 25(3 & 4), pp. 401-418.

Clore, G. L., Schwarz, N. & Conway, M., 1994. Affective Causes and Consequences of Social Information Processing . In: *Handbook of Social Cognition* . Second Edition ed. Hillsdale (New Jersey): Lawrence Erlbaum Associates , p. 386.

Compustat, n.d. *Compustat Global - Security Daily*. [Online]
Available at: https://wrds-web.wharton.upenn.edu/wrds/ds/compd/g_secd/index.cfm?navId=73
[Accessed 10 February 2020].

Connolly, R. A., 1989. An Examination of the Robustness of the Weekend Effect. *The Journal of Financial and Quantitative Analysis*, June, 24(2), pp. 133-169.

Connolly, R. A., 1991. A posterior odds analysis of the weekend effect. *Journal of Econometrics*, July-August, 49(1-2), pp. 51-104.

Cross, F., 1973. The Behavior of Stock Prices on Fridays and Mondays. *Financial Analysts Journal*, Volume 29, pp. 67-69.

Da, Z., Engelberg, J. & Gao, P., 2015. The Sum of All FEARS Investor Sentiment and Asset Prices. *The Review of Financial Studies*, January, 28(1), pp. 1-32.

Dubois, M. & Louvet, P., 1996. The day-of-the-week effect: The international evidence. *Journal of Banking & Finance*, November, 20(9), pp. 1463-1484.

Egloff, B., Tausch, A., Kohlmann, C.-W. & Krohne, H. W., 1995. Relationships between time of day, day of the week, and positive mood: Exploring the role of the mood measure. *Motivation and Emotion*, 19(2), pp. 99-110.

Fisher, K. L. & Statman, M., 2000. Investor Sentiment and Stock Returns. *Financial Analysts Journal*, March, 56(2), pp. 16-23.

French, K. R., 1980. Stock Returns and the Weekend Effect. *Journal of Financial Economics*, March, 8(1), pp. 55-69.

Gayaker, S., Yalcin, Y. & Berument, M. H., 2020. The day of the week effect and interest rates. *Borsa Istanbul Review*, March, 20(1), pp. 55-63.

Gibbons, M. R. & Hess, P., 1981. Day of the Week Effects and Asset Returns. *The Journal of Business* , 54(4), pp. 579-596.

Hao, Y., Chou, R. K., Ko, K.-C. & Yang, N.-T., 2018. The 52-week high, momentum, and investor sentiment. *International Review of Financial Analysis*, May, Volume 57, pp. 167-183.

Hou, K., Xue, C. & Zhang, L., 2015. Digesting Anomalies: An Investment Approach. *The Review of Financial Studies*, March, 28(3), pp. 650-705.

James, G., Witten, D., Hastie, T. & Tibshirani, R., 2017. *An Introduction to Statistical Learning.* Palo Alto, USA: Springer.

Kelly, F. C., 1930. *Why You Win or Lose: The Psychology of Speculation.* Boston(MA): Houghton Mifflin Company .

Kumar, A., 2009. Who Gambles in the Stock Market?. *The Journal of Finance,* August , 64(4), pp. 1889-1993.

Norges Bank, n.d. *Interest rates.* [Online]
Available at: https://www.norges-bank.no/en/topics/Statistics/Interest-rates/
[Accessed 03 March 2020].

Oslo Børs, 2013. *Oslo Børs VPS innfører raskere oppgjør fra oktober 2014.* [Online]
Available at: https://www.oslobors.no/Oslo-Boers/Om-Oslo-Boers/Nyheter-fra-Oslo-Boers/Oslo-Boers-VPS-innfoerer-raskere-oppgjoer-fra-oktober-2014
[Accessed 8 March 2020].

Oslo Børs, n.d. *Hovedindeksen.* [Online]
Available at: https://www.oslobors.no/markedsaktivitet/#/details/OSEBX.OSE/overview
[Accessed 10 April 2020].

Oslo Børs, n.d. *Månedsstatistikk.* [Online]
Available at: https://www.oslobors.no/Oslo-Boers/Statistikk/Maanedsstatistikk/(index)/2/(year)/2019
[Accessed 23 May 2020].

Reid, S., Towell, A. & Golding, J., 2000. Seasonality, social zeitgebers and mood variability in entrainment of mood Implications for seasonal affective disorder. *Journal of Affective Disorders,* July, 59(1), pp. 47-54.

Rosenberg, B., Reid, K. & Lanstein, R., 1985. Persuasive evidence of market inefficiency. *The Journal of Portfolio Management*, 11(3), pp. 9-17.

Rystrom, D. S. & Benson, E. D., 1989. Investor Psychology and the Day-of-the-Week effect. *Financial Analysts Journal,* September-October, 45(5), pp. 75-77.

Wooldridge, J. M., 2018. *Introductory Econometrics.* Michigan: Cengage Learning.

Wright, W. F. & Bower, G. H., 1992. Mood Effects on Subjective Probability Assessment. *Organizational Behavior and Human Decision Processes*, July, 52(2), pp. 276-291.

Zilca, S., 2017. The evolution and cross-section of the day-of-the-week effect. *Financial Innovation 3*, November, Volume 29, pp. 1-12.

8. Appendix

8.1 Davidson-MacKinnon test for non-nested models

We test the following equations to determine the best goodness of fit.

Two-sided t-test of the fitted value $\tilde{y}$ from the linear equation (size and price as linear), in the logarithmic equation (price and size as logarithms).	Two-sided t-test, of the fitted value $\hat{y}$ from the logarithmic equation (price and size as logarithms), in the linear equation (price and size as linear).
F(1, 269) = 2.73 Prob > F = 0.1000	F(1, 269) = 97.34 Prob > F = 0.0000

Thus, we reject at the 5%-level of significance that $\hat{y} = 0$ but we do not have evidence to reject at the 5%-level of significance that $\tilde{y} = 0$. This indicates that we prefer the model with price and size as logarithms.

8.2 Testing for Heteroscedasticity

The Wald and Breusch Pagan tests for all equations show clear signs of heteroscedasticity.

	Fixed Effect – Wald Test H0: Constant variance	Pooled OLS – Breusch Pagan H0: Constant variance
Equation 1:	Prob > chi2 = 0.0000	Prob > chi2 = 0.0000
Equation 2:	Prob > chi2 = 0.0000	Prob > chi2 = 0.0000
Equation 3:	Prob > chi2 = 0.0000	Prob > chi2 = 0.0000
Equation 4:	Prob > chi2 = 0.0000	Prob > chi2 = 0.0000
Equation 5:	Prob>chi2 = 0.0000	Prob > chi2 = 0.0000
Equation 6:	Prob>chi2 = 0.0000	Prob > chi2 = 0.0000

8.3 Wooldridge Test for Autocorrelation

Equations 1, 2, 3 and 6 show signs of autocorrelation. Equations 4 and 5 do not.

	Wooldridge test for autocorrelation H0: No first-order autocorrelation
Equation 1:	Prob > F = 0.0267
Equation 2:	Prob > F = 0.0266
Equation 3:	Prob > F = 0.0267
Equation 4:	Prob > F = 0.1214
Equation 5:	Prob > F = 0.1212
Equation 6:	Prob > F = 0.0267

8.4 Variance Inflation Factor Tests

Equation 1

Monday	Friday
1.065196	1.065196

Equation 2

Monday	Friday	SentimentScore	Monday*SentimentScore	Friday*SentimentScore
10.921735	10.948341	1.657674	11.185505	11.216073

Equation 3

Monday	Friday	Earnings	WBeta	WROA
270.221775	270.369664	2.562505	1.856341	2.196935
lnPrice	lnsize	Age	MaxReturn	Illiquidity
3.941099	4.366022	1.926586	1.894601	1.734744
FiftyTwo	Monday*Earnings	Monday*WBeta	Monday*WROA	Monday*lnPrice
1.746944	4.327365	3.300574	1.794913	10.890397
Monday*lnsize	Monday*Age	Monday*MaxReturn	Monday*Illiquidity	Monday*FiftyTwo
359.440132	2.523365	1.655656	1.386292	1.820268
Friday*Earnings	Friday*WBeta	Friday*WROA	Friday*lnPrice	Friday*lnsize
4.336969	3.305737	1.798604	359.369379	10.936871
Friday*Age	Friday*MaxReturn	Friday*Illiquidity	Friday*FiftyTwo	
2.522661	1.520141	1.357065	1.826489	

Equation 4

Monday	Friday	SettlementChange	Monday*SettlementChange	Friday*SettlementChange
1.487125	1.478154	1.658368	1.751343	1.742800

Equation 5

Monday	Friday	PutsDummy	Monday*PutsDummy	Friday*PutsDummy
1.174898	1.174181	1.657053	1.435197	1.440465

Equation 6

Monday	Friday	PutsDummy	SentimentScore	SettlementChange
13.07	13.08	1.81	1.81	1.66
Monday*PutsDummy	Monday*SentimentScore	Monday*SettlementChange		
1.59	12.22	1.9		
Friday*PutsDummy	Friday*SentimentScore	Friday*SettlementChange		
1.59	12.24	1.89		

8.5 Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Beta	1.000								
(2) ROA	-0.033	1.000							
(3) lnPrice	-0.013	0.356	1.000						
(4) lnSize	0.201	0.326	0.717	1.000					
(5) Earnings	-0.056	0.463	0.489	0.441	1.000				
(6) Age	0.067	0.100	0.175	0.354	0.113	1.000			
(7) MaxReturn	-0.003	-0.095	-0.132	-0.127	-0.105	-0.031	1.000		
(8) Illiquidity	-0.007	-0.028	-0.057	-0.063	-0.035	-0.005	0.011	1.000	
(9) 52WH	0.036	-0.152	-0.184	-0.153	-0.177	-0.039	0.083	-0.000	1.000

8.6 Testing Equation 3 for Effects of Multicollinearity

Equation 3 results

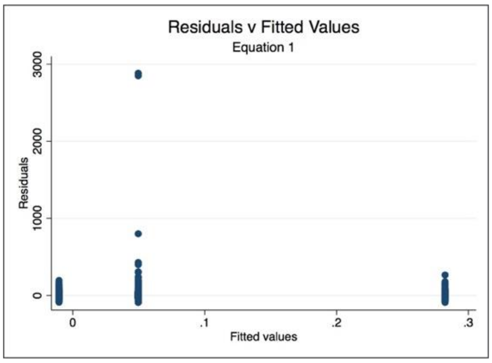
Equation 3 is presented with Fixed Effect and pooled OLS estimators. Both lnPrice and lnSize are included in sub-equations 1 and 2, while sub-equations 3 and 4 are estimated without lnSize, and sub-equations 5 and 6 are estimated without lnPrice. Standard errors are clustered by company in all estimations. Robust standard errors are presented in parentheses.

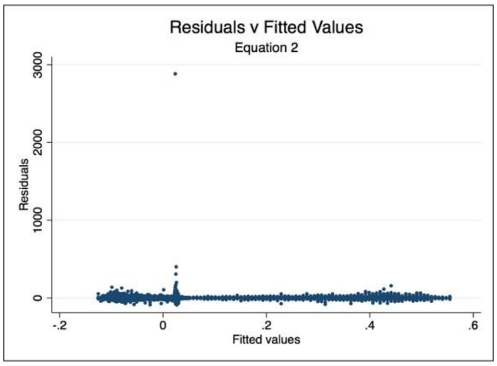
	(1) Fixed Effect Both Returns	(2) Pooled OLS Both Returns	(3) Fixed Effect W/O Size Returns	(4) Pooled OLS W/O Size Returns	(5) Fixed Effect W/O Price Returns	(6) Pooled OLS W/O Price Returns
Monday	0.28967	0.29388	-0.08548	-0.08279	-0.18271	-0.17628
	(0.35973)	(0.36115)	(0.06045)	(0.06047)	(0.29728)	(0.29870)
Earnings	0.06569***	0.07890***	0.02882	0.06252***	0.06457***	0.07273***
	(0.02502)	(0.02192)	(0.02765)	(0.02170)	(0.02459)	(0.02198)
Beta	-0.02184	-0.01164	-0.04386**	-0.03904**	-0.02163	-0.00716
	(0.01909)	(0.01686)	(0.02211)	(0.01783)	(0.01949)	(0.01691)
ROA	0.96380***	0.54419***	0.66621**	0.50087**	0.95309***	0.52846***
	(0.24801)	(0.19912)	(0.25921)	(0.19727)	(0.24665)	(0.19989)
Age	0.00379	0.00305*	-0.00566**	0.00179	0.00326	0.00317*
	(0.00347)	(0.00168)	(0.00267)	(0.00132)	(0.00332)	(0.00162)
lnPrice	0.00562	-0.01156	-0.10463***	-0.03941***		
	(0.02038)	(0.01002)	(0.01682)	(0.00755)		
lnSize	-0.17745***	-0.04089**			-0.17208***	-0.04785***
	(0.02962)	(0.01685)			(0.02068)	(0.01316)
MaxReturn	-0.12523	-0.07316	-0.10620	-0.06345	-0.12491	-0.07075
	(0.09080)	(0.07502)	(0.08067)	(0.07125)	(0.08990)	(0.07251)
52WeekHigh	0.01990**	0.01407	0.02031**	0.01438	0.01983**	0.01432
	(0.00920)	(0.00992)	(0.00945)	(0.01012)	(0.00914)	(0.00985)
Illiquidity	10.11335	14.03636	21.88128	25.20259	10.37502	15.29749
	(44.02701)	(43.87139)	(45.05213)	(46.65077)	(44.13303)	(44.67679)
Monday*Earnings	-0.01620	-0.01672	-0.02457	-0.02548	0.00966	0.00907
	(0.04806)	(0.04816)	(0.04823)	(0.04829)	(0.04824)	(0.04830)
Monday*Beta	-0.00362	-0.00487	-0.01753	-0.01875	-0.02260	-0.02376
	(0.03270)	(0.03285)	(0.03289)	(0.03307)	(0.03291)	(0.03307)
Monday*ROA	0.36452	0.36468	0.34023	0.34105	0.43148	0.43129
	(0.49034)	(0.49076)	(0.49662)	(0.49754)	(0.49058)	(0.49092)
Monday*Age	-0.00193	-0.00193	-0.00257	-0.00257	-0.00243	-0.00243
	(0.00197)	(0.00198)	(0.00158)	(0.00159)	(0.00188)	(0.00189)
Monday*lnPrice	0.04888***	0.04867***	0.03449**	0.03442**		
	(0.01718)	(0.01719)	(0.01349)	(0.01350)		
Monday*lnSize	-0.02075	-0.02081			0.00872	0.00853
	(0.01984)	(0.01990)			(0.01528)	(0.01534)
Monday*MaxReturn	0.11574	0.10706	0.11284	0.10714	0.10878	0.09948
	(0.09360)	(0.08892)	(0.09466)	(0.09168)	(0.08868)	(0.08373)
Monday*52WeekHigh	-0.00940	-0.00951	-0.00910	-0.00933	-0.01043	-0.01055
	(0.01600)	(0.01605)	(0.01603)	(0.01607)	(0.01600)	(0.01605)
Monda*Illiquidity	-37.62345	-36.67682	-31.97048	-31.77012	-42.31780	-41.49683
	(82.46578)	(83.02645)	(83.76265)	(84.04999)	(79.83254)	(80.32850)
Friday	0.47747	0.47896	0.39256***	0.39100***	0.73285**	0.73370**
	(0.35339)	(0.35313)	(0.06016)	(0.06023)	(0.28949)	(0.28912)
Friday*Earnings	-0.09828**	-0.09706**	-0.10026**	-0.09929**	-0.11224**	-0.11090**
	(0.04303)	(0.04306)	(0.04309)	(0.04318)	(0.04332)	(0.04331)
Friday*Beta	0.01869	0.01861	0.01577	0.01554	0.02892	0.02879
	(0.04070)	(0.04079)	(0.03848)	(0.03859)	(0.03997)	(0.04008)
Friday*ROA	-0.30414	-0.30263	-0.30730	-0.30657	-0.34114	-0.33983
	(0.37279)	(0.37231)	(0.37924)	(0.37892)	(0.36352)	(0.36308)
Friday*Age	-0.00264	-0.00264	-0.00279*	-0.00279*	-0.00237	-0.00236
	(0.00184)	(0.00184)	(0.00156)	(0.00156)	(0.00184)	(0.00183)
Friday*lnPrice	-0.02656	-0.02652	-0.02994**	-0.02983**		
	(0.01750)	(0.01748)	(0.01337)	(0.01336)		
Friday*lnSize	-0.00471	-0.00486			-0.02068	-0.02080
	(0.01938)	(0.01935)			(0.01474)	(0.01470)
Friday*MaxReturn	0.07479	0.07671	0.07623	0.07800	0.08041	0.08235
	(0.11392)	(0.11514)	(0.11693)	(0.11804)	(0.11658)	(0.11784)
Friday*52WeekHigh	0.00140	0.00159	0.00142	0.00161	0.00197	0.00216
	(0.01278)	(0.01272)	(0.01279)	(0.01274)	(0.01279)	(0.01274)
Friday*Illiquidity	99.92262	99.10922	101.56278	100.26629	102.63757	101.76252
	(144.31854)	(143.80520)	(144.42360)	(143.91222)	(145.95107)	(145.45027)

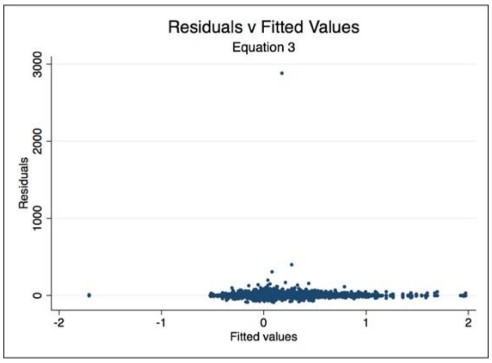
_cons	3.67676***	0.83644***	0.38988***	0.09506***	3.58651***	0.94790***
	(0.54824)	(0.30591)	(0.05493)	(0.02634)	(0.40601)	(0.24927)
Obs.	400273	400273	400273	400273	400273	400273
Adj. R-squared	0.00088	0.00053	0.00065	0.00046	0.00087	0.00052

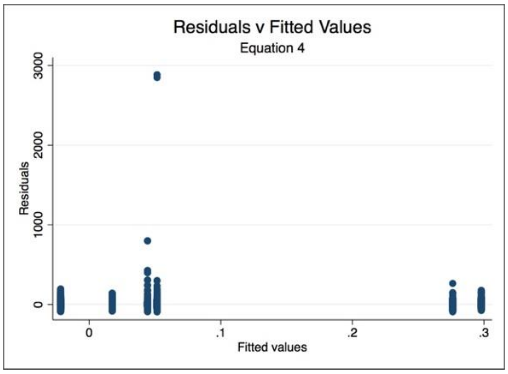
Standard errors are in parenthesis
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

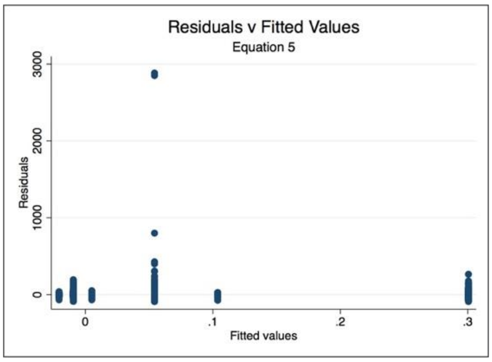
8.7 Residuals Versus Fitted Values

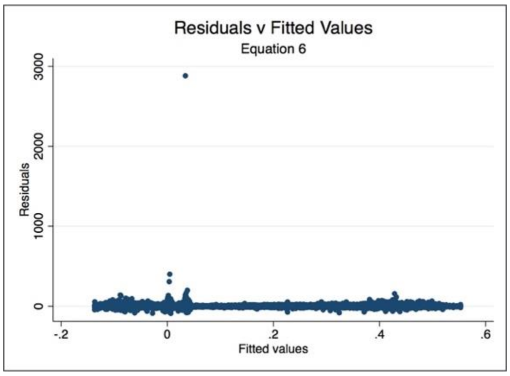












8.8 Yearly and Industry Fixed Effects

Equation 1 Results

Equation 1 is presented below, in which equation 1 is presented with a Fixed Effect estimator, with and without yearly fixed effects, and pooled OLS estimator are presented with and without yearly and industry fixed effects.

	(1) Fixed Effect Returns	(2) Fixed Effect Returns	(3) Pooled OLS Returns	(4) Pooled OLS Returns
Monday	-0.05921**	-0.06007**	-0.06005**	-0.06251**
	(0.02383)	(0.02402)	(0.02456)	(0.02488)
Friday	0.23309***	0.23400***	0.23270***	0.23393***
	(0.02218)	(0.02216)	(0.02210)	(0.02207)
_cons	0.04933***	-0.09500**	0.04957**	-0.08135
	(0.00761)	(0.04022)	(0.01988)	(0.05180)
Obs.	553181	553181	553181	551250
Adj. R-squared	0.00019	0.00078	0.00019	0.00080
Unit Dummy:	YES	YES	NO	NO
Industry Dummy:	NO	NO	NO	YES
Yearly Dummy:	NO	YES	NO	YES

Standard errors are in parenthesis
****p<0.01, **p<0.05, *p<0.1*

Equation 2 Results

Equation 2 is presented below, in which equation 2 is presented with a Fixed Effect estimator, with and without yearly fixed effects, and pooled OLS estimator are presented with and without yearly and industry fixed effects.

	(1) Fixed Effect Returns	(2) Fixed Effect Returns	(3) Pooled OLS Returns	(4) Pooled OLS Returns
Monday	0.05357	0.05332	0.05357	0.05374
	(0.08188)	(0.08158)	(0.08180)	(0.08162)
SentimentScore	0.03274	0.02661	-0.00115	0.00058
	(0.03060)	(0.02986)	(0.01277)	(0.01389)
Mon*SentimentScore	-0.02036	-0.02038	-0.02031	-0.02049
	(0.01794)	(0.01796)	(0.01793)	(0.01797)
Friday	-0.11008	-0.10832	-0.10977	-0.10839
	(0.07364)	(0.07375)	(0.07372)	(0.07383)
Fri*SentimentScore	0.06503***	0.06480***	0.06496***	0.06490***
	(0.01621)	(0.01624)	(0.01623)	(0.01626)
_cons	-0.14718	-0.66660***	0.03355	-0.46287***
	(0.15920)	(0.14366)	(0.05673)	(0.09582)
Obs.	400273	400273	400273	399941
Adj. R-squared	0.00037	0.0010	0.00034	0.0010
Unit Dummy:	YES	YES	NO	NO
Industry Dummy:	NO	NO	NO	YES
Yearly Dummy:	NO	YES	NO	YES

Standard errors are in parenthesis
****p<0.01, **p<0.05, *p<0.1*

Equation 3 Results

Equation 3 is presented below, in which equation 3 is presented with a Fixed Effect estimator, with and without yearly fixed effects, and pooled OLS estimator are presented with and without yearly and industry fixed effects.

	(1) Fixed Effect Returns	(2) Fixed Effect Returns	(3) Pooled OLS Returns	(4) Pooled OLS Returns
Monday	0.28967	0.29323	0.29388	0.29121
	(0.35973)	(0.36008)	(0.36115)	(0.36197)
Earnings	0.06569***	0.04519*	0.07890***	0.05574***
	(0.02502)	(0.02334)	(0.02192)	(0.01973)
Beta	-0.02184	-0.02734	-0.01164	-0.01342
	(0.01909)	(0.01855)	(0.01686)	(0.01607)
ROA	0.96380***	0.88343***	0.54419***	0.54754***
	(0.24801)	(0.24165)	(0.19912)	(0.19400)
Age	0.00379	0.02925***	0.00305*	0.00225
	(0.00347)	(0.00232)	(0.00168)	(0.00149)
lnPrice	0.00562	0.00921	-0.01156	-0.00647
	(0.02038)	(0.01919)	(0.01002)	(0.00929)
lnSize	-0.17745***	-0.13502***	-0.04089**	-0.03100**
	(0.02962)	(0.02872)	(0.01685)	(0.01548)
MaxReturn	-0.12523	-0.11210	-0.07316	-0.06233
	(0.09080)	(0.07615)	(0.07502)	(0.06056)
52WeekHigh	0.01990**	0.02099**	0.01407	0.01572
	(0.00920)	(0.01008)	(0.00992)	(0.01067)
Illiquidity	10.11335	12.64068	14.03636	18.72453
	(44.02701)	(46.59683)	(43.87139)	(47.48899)
Monday*Earnings	-0.01620	-0.01683	-0.01672	-0.01818
	(0.04806)	(0.04812)	(0.04816)	(0.04821)
Monday*Beta	-0.00362	-0.00345	-0.00487	-0.00489
	(0.03270)	(0.03265)	(0.03285)	(0.03280)
Monday*ROA	0.36452	0.36514	0.36468	0.36396
	(0.49034)	(0.49011)	(0.49076)	(0.49044)
Monday*Age	-0.00193	-0.00193	-0.00193	-0.00191
	(0.00197)	(0.00197)	(0.00198)	(0.00198)
Monday*lnPrice	0.04888***	0.04921***	0.04867***	0.04897***
	(0.01718)	(0.01715)	(0.01719)	(0.01716)
Monday*lnSize	-0.02075	-0.02096	-0.02081	-0.02074
	(0.01984)	(0.01982)	(0.01990)	(0.01989)
Monday*MaxReturn	0.11574	0.10976	0.10706	0.10082
	(0.09360)	(0.09098)	(0.08892)	(0.08629)
Monday*52WeekHigh	-0.00940	-0.00921	-0.00951	-0.00917
	(0.01600)	(0.01600)	(0.01605)	(0.01603)
Monday*Illiquidity	-37.62345	-40.43221	-36.67682	-39.78898
	(82.46578)	(81.77529)	(83.02645)	(82.19951)
Friday	0.47747	0.47654	0.47896	0.48712
	(0.35339)	(0.35368)	(0.35313)	(0.35330)
Friday*Earnings	-0.09828**	-0.09889**	-0.09706**	-0.09686**
	(0.04303)	(0.04298)	(0.04306)	(0.04301)
Friday*Beta	0.01869	0.01789	0.01861	0.01814
	(0.04070)	(0.04069)	(0.04079)	(0.04077)
Friday*ROA	-0.30414	-0.30174	-0.30263	-0.29885
	(0.37279)	(0.37284)	(0.37231)	(0.37264)
Friday*Age	-0.00264	-0.00264	-0.00264	-0.00265
	(0.00184)	(0.00184)	(0.00184)	(0.00184)
Friday*lnPrice	-0.02656	-0.02643	-0.02652	-0.02606
	(0.01750)	(0.01750)	(0.01748)	(0.01748)
Friday*lnSize	-0.00471	-0.00464	-0.00486	-0.00525
	(0.01938)	(0.01939)	(0.01935)	(0.01935)
Friday*MaxReturn	0.07479	0.07513	0.07671	0.07690
	(0.11392)	(0.11409)	(0.11514)	(0.11526)
Friday*52WeekHigh	0.00140	0.00142	0.00159	0.00156
	(0.01278)	(0.01278)	(0.01272)	(0.01274)
Friday*Illiquidity	99.92262	99.07873	99.10922	97.46354
	(144.31854)	(143.99051)	(143.80520)	(143.12878)
_cons	3.67676***	2.33279***	0.83644***	0.17760
	(0.54824)	(0.56663)	(0.30591)	(0.26941)
Obs.	400273	400273	400273	399941
R-squared	0.00065	0.0012	0.00046	0.0011
Unit Dummy:	YES	YES	NO	NO
Industry Dummy:	NO	NO	NO	YES
Yearly Dummy:	NO	YES	NO	YES

Standard errors are in parenthesis

*** *p*<0.01, ** *p*<0.05, * *p*<0.1

Equation 4 Results

Equation 4 is presented below, in which equation 4 is presented with a Fixed Effect estimator, with and without yearly fixed effects, and pooled OLS estimator are presented with and without yearly and industry fixed effects. The base Fixed Effects estimation model uses unit fixed effects to remove all between-unit variation.

	(1) Returns100	(2) Returns100	(3) Returns100	(4) Returns100
Monday	-0.07238***	-0.07383***	-0.07322***	-0.07691***
	(0.02768)	(0.02806)	(0.02794)	(0.02854)
SettlementChange	-0.08318***	-0.20433	-0.00723	-0.20705
	(0.03213)	(0.16541)	(0.02201)	(0.16527)
Mon*SettlementChange	0.04665	0.04815	0.04636	0.05023
	(0.03952)	(0.03979)	(0.03970)	(0.03998)
Friday	0.22584***	0.22716***	0.22461***	0.22611***
	(0.02841)	(0.02839)	(0.02853)	(0.02863)
Fri*SettlementChange	0.02549	0.02413	0.02895	0.02755
	(0.04268)	(0.04273)	(0.04335)	(0.04358)
_cons	0.07274***	-0.09088**	0.05160**	-0.07696
	(0.01483)	(0.04029)	(0.02013)	(0.05252)
Obs.	553181	553181	553181	551250
Adj. R-squared	0.00020	0.00078	0.00018	0.00080
Unit Dummy:	YES	YES	NO	NO
Industry Dummy:	NO	NO	NO	YES
Yearly Dummy:	NO	YES	NO	YES

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Equation 5 Results

Equation 5 is presented below, in which equation 5 is presented with a Fixed Effect estimator, with and without yearly fixed effects, and pooled OLS estimator are presented with and without yearly and industry fixed effects.

	(1) Fixed Effect Returns	(2) Fixed Effect Returns	(3) Pooled OLS Returns	(4) Pooled OLS Returns
Monday	-0.06279**	-0.06370**	-0.06373**	-0.06640**
	(0.02611)	(0.02631)	(0.02692)	(0.02726)
PutsDummy	-0.05208	-0.04002	-0.04924	-0.04983
	(0.03288)	(0.03511)	(0.03099)	(0.03334)
Monday*PutsDummy	0.03707	0.03734	0.03807	0.03994
	(0.03587)	(0.03589)	(0.03649)	(0.03657)
Friday	0.24671***	0.24763***	0.24627***	0.24758***
	(0.02406)	(0.02403)	(0.02398)	(0.02396)
Friday*PutsDummy	-0.14767***	-0.14773***	-0.14746***	-0.14778***
	(0.03818)	(0.03819)	(0.03802)	(0.03811)
_cons	0.05424***	-0.09229**	0.05423**	-0.07541
	(0.00898)	(0.03962)	(0.02184)	(0.05374)
Obs.	552938	552938	552938	551007
Adj. R-squared	0.00019	0.00078	0.00019	0.00081
Unit Dummy:	YES	YES	NO	NO
Industry Dummy:	NO	NO	NO	YES
Yearly Dummy:	NO	YES	NO	YES

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

Equation 6 Results

Equation 6 is presented below, in which equation 6 is presented with a Fixed Effect estimator, with and without yearly fixed effects, and pooled OLS estimator are presented with and without yearly and industry fixed effects.

	(1) Fixed Effect Returns	(2) Fixed Effect Returns	(3) Pooled OLS Returns	(4) Pooled OLS Returns
Monday	0.04449	0.04377	0.04421	0.04376
	(0.08509)	(0.08465)	(0.08504)	(0.08472)
SettlementChange	-0.06852**	-0.04453	-0.03238	-0.04855
	(0.02994)	(0.06142)	(0.02422)	(0.06160)
PutsDummy	-0.01759	-0.04810	-0.01398	-0.01276
	(0.04095)	(0.03908)	(0.02643)	(0.02993)
SentimentScore	0.03429	0.02697	-0.00183	-0.00026
	(0.03071)	(0.03010)	(0.01340)	(0.01470)
Mon*SettlementChange	0.05170	0.05268	0.05207	0.05356
	(0.03878)	(0.03916)	(0.03875)	(0.03918)
Mon*PutsDummy	-0.02283	-0.02286	-0.02265	-0.02250
	(0.03445)	(0.03450)	(0.03451)	(0.03457)
Mon*SentimentScore	-0.02157	-0.02158	-0.02149	-0.02167
	(0.01871)	(0.01872)	(0.01869)	(0.01873)
Friday	-0.09583	-0.09352	-0.09566	-0.09327
	(0.07814)	(0.07821)	(0.07822)	(0.07829)
Fri*SettlementChange	0.01503	0.01396	0.01563	0.01362
	(0.03964)	(0.03981)	(0.03965)	(0.03981)
Fri*PutsDummy	-0.05413*	-0.05472*	-0.05442*	-0.05534*
	(0.03051)	(0.03051)	(0.03049)	(0.03048)
Fri*SentimentScore	0.06242***	0.06217***	0.06234***	0.06224***
	(0.01687)	(0.01690)	(0.01689)	(0.01692)
_cons	-0.12999	-0.65931***	0.04986	-0.44792***
	(0.15591)	(0.14324)	(0.05699)	(0.10217)
Obs.	400030	400030	400030	399698
Adj. R-squared	0.00037	0.00099	0.00033	0.0010
Unit Dummy:	YES	YES	NO	NO
Industry Dummy:	NO	NO	NO	YES
Yearly Dummy:	NO	YES	NO	YES

Standard errors are in parenthesis
**** p<0.01, ** p<0.05, * p<0.1*

8.9 Augmented Dickey-Fuller Test

An Augmented Dickey-Fuller Test is run on the returns. This indicates stationarity.

Dickey-Fuller = -431.23	Lag order = 2,
p-value = 0.01	H0: Non-stationarity

8.10 List of Companies in Dataset

Company	ISIN	Company	ISIN
24SEVEN TECHNOLOGY GROUP	NO0010279474	BWG HOMES ASA	NO0010298300
A-PRESSEN AS	NO0005014001	BYGGMA ASA	NO0003087603
ABILITY DRILLING ASA	NO0010333024	CARASENT ASA	NO0010123060
ACTINOR SHIPPING	NO0003028607	CATCH COMMUNICATIONS AS	NO0010093933
ADEVINTA ASA	NO0010844038	CECON AS	NO0010355910
ADVANCED PROD & LOADING	NO0010255862	CELLCURA ASA	NO0010386253
AEGA ASA	NO0010626559	CERMAQ ASA	NO0010003882
AF GRUPPEN ASA	NO0003078107	CHOICE HOTELS SCANDINAVIA	NO0003072506
AGR GROUP ASA	NO0010277171	CODFARMERS ASA	NO0010160484
AGRESSO GROUP ASA	NO0003052508	COMPELLO AS	NO0010322324
AGRINOS AS	NO0010592934	COMPONENT SOFTWARE GROUP ASA	NO0010068513
AKASTOR ASA	NO0010215684	COMROD COMMUNICATIONS ASA	NO0010338445
AKER BIOMARINE ASA	NO0003084006	CONFORMIT ASA	NO0003117509
AKER BP ASA	NO0010295603	COPEINCA ASA	NO0010352412
AKER DRILLING ASA SHS	NO0010287006	CRAYON GROUP HOLDING ASA	NO0010026230
AKER FLOATING PRODUCTION ASA	NO0010308836	CRUDECORP ASA	NO0010368475
AKER MARITIME ASA	NO0003062507	CRYSTAL PRODUCTION ASA	NO0003015901
AKER SOLUTIONS ASA	NO0010716582	CUSTOMAX ASA	NO0003111809
AKVA GROUP ASA	NO0003097503	CXENSE ASA	NO0010671068
ALCATEL STK ASA	NO0005487207	DATA RESPONSE ASA	NO0003064107
ALGETA ASA	NO0010239437	DEEP OCEAN ASA	NO0010279821
ALTINEX ASA	NO0003056806	DEEP SEA SUPPLY ASA	NO0010226905
ALVERN ASA	NO0003050304	DNO ASA	NO0003921009
AMERICAN SHIPPING CO ASA	NO0010272065	DOF ASA	NO0010070063
ANDVORD TYBRING-GJEDDE ASA	NO0005724401	DOF INSTALLER ASA	NO0010359565
AQUA BIO TECHNOLOGY ASA	NO0010307135	DOF SUBSEA ASA	NO0010274608
AQUALISBRAEMAR ASA	NO0010715394	DOLPHIN DRILLING ASA	NO0003089005
ARACA ENERGY ASA	NO0010318405	DOLPHIN GROUP ASA	NO0010170921
ARCUS ASA	NO0010776875	DOMSTEIN ASA	NO0003072407
ARENDALS FOSSEKOMPANI ASA	NO0003572802	DSND SUBSEA ASA	NO0003143604
ASK PROXIMA ASA	NO0005621201	DYNO ASA	NO0003983702
ASKER OG BAERUMS BUDSTIKKE	NO0003586802	EAM SOLAR ASA	NO0010607781
ATEA ASA	NO0004822503	EASTERN DRILLING ASA	NO0010265168
ATLANTIC LUMPUS AS	NO0010755051	EIDESVIK OFFSHORE ASA	NO0010263023
ATLANTIC SAPPHIRE	NO0010768500	EIENDOMSSPAR ASA	NO0003998700
AURORA LPG HOLDING ASA	NO0010701279	EITZEN CHEMICAL ASA	NO0010327620
AUSTEVOLL SEAFOOD ASA	NO0010073489	EKORNES ASA	NO0003035305
AVENIR ASA	NO0005598706	ELECTROMAGNETIC GEOSERV	NO0010358484
AWILCO ASA	NO0003083107	ELEMENT ASA	NO0003055808
AWILCO LNG AS	NO0010607971	ELKEM ASA	NO0010816093
AWILCO OFFSHORE ASA	NO0010255722	ELKEM GROUP A/S	NO0004031303
AXXIS GEO SOLUTIONS AS	NO0010778095	ELKJOP ASA	NO0003042202
BALTIC SEA PROP AS	NO0010810476	ELTEK ASA	NO0003109407
BELSHIPS ASA	NO0003094104	EMS SEVEN SEAS ASA	NO0003075905
BERGEN NORDHORDLAND RUTELAG	NO0003099608	ENDUR ASA	NO0010379779
BERGENBIO ASA	NO0010650013	ENITEL ASA	NO0003098402
BERGESEN DY A/S	NO0003102113	ENTRA ASA	NO0010716418
BIOTEC PHARMACON	NO0010014632	ENWA ASA	NO0010097041
BJOLVEFOSSEN AS	NO0003666604	EQOLOGY ASA	NO0010585144
BJORGE GRUPPEN ASA	NO0003101404	EQUINOR ASA	NO0010096985
BLACK SEA PROPERTY AS	NO0010755101	ETMAN INTERNATIONAL AS	NO0010130743
BONHEUR A/S	NO0003110603	EUROPRIS ASA	NO0010735343
BORGESTAD ASA	NO0003111700	EVERCOM NETWORK ASA	NO0003081101
BORGESTAD INDUSTRIES	NO0010439813	EVRY ASA	NO0010019649
BORREGAARD ASA	NO0010657505	EXENSE ASA	NO0003116709
BOUVET ASA	NO0010360266	EXPERT ASA	NO0003089104
BRAATHENS ASA	NO0003044703	FARA ASA	NO0010296007
BRIDGE ENERGY ASA	NO0010566235	FARSTAD SHIPPING ASA	NO0003215303
BULK INVEST ASA	NO0003042905	FAST SEARCH AND TRANSFER AS	NO0003109605

FESIL ASA	NO0003046906	KRISTIANSAND DYREPARK ASA	NO0003033300
FJORD SEAFOOD ASA	NO0003102600	KVAERNER ASA	NO0010605371
FJORD1 ASA	NO0010792625	KVAERNER ASA (OLD)	NO0004684408
FJORDKRAFT HLDG	NO0010815673	KVERNELAND ASA	NO0004677006
FOSEN ASA	NO0003168908	LAVO.TV AS	NO0010793326
FRED OLSEN PRODUCTION AS	NO0010354020	LEIF HOEGH & CO ASA	NO0004456906
FRONTIER DRILLING AS	NO0010067713	LEROY SEAFOOD GROUP ASA	NO0003096208
GAMING INNOVATION GROUP INC	US36467X2062[1]	LIFECARE AS	NO0010591191
GANGER ROLF A/S	NO0003172207	LINDE-GROUP ASA	NO0003082406
GC RIEBER SHIPPING ASA	NO0010262686	LINK MOBILITY GROUP ASA	NO0010219702
GENTIAN DIAGNOSTIC AS	NO0010748866	LIONERO AS	NO0010298318
GOLDEN CLOSE MARIT	BMG4026X1020	LOKI ASA	NO0003088700
GOLDEN ENERGY OFFSHORE	NO0010813843	LUXO ASA	NO0003106007
GOODTECH ASA	NO0004913609	MAGNORA ASA	NO0010187032
GREGOIRE ASA	NO0010375298	MAGSEIS FAIRFIELD ASA	NO0010663669
GRENLAND GROUP ASA	NO0010285661	MAMUT ASA	NO0003105405
GRESVIG ASA	NO0003046401	MARINE FARMS ASA	NO0010049059
GRIEG SEAFOOD AS	NO0010365521	MEDIABIN INC	US58446U2024
GYLDENDAL ASA	NO0004288200	MEDISTIM ASA	NO0010159684
HAFSLUND ASA	NO0004306416	MEFJORDEN AS	NO0010028889
HAG ASA	NO0004474503	MOELVEN INDUSTRIER ASA	NO0004845405
HANDS ASA	NO0010065154	MORPOL ASA	NO0010577299
HAVFISK ASA	NO0010269129	MOWI ASA	NO0003054108
HAVILA SHIPPING ASA	NO0010257728	MPC CONTAINER SHIPS ASA	NO0010791353
HAVILA SUPPLY ASA	NO0003107104	MULTICLIENT GEOPHYSICAL ASA	NO0010657604
HAVYARD GROUP ASA	NO0010708605	MULTICONSULT ASA	NO0010734338
HEXAGON COMPOSITES ASA	NO0003067902	MULTIPOWER ASA	NO0010139348
HIDDN SOLUTIONS ASA	NO0003108102	NATTOPHARMA ASA	NO0010289200
HITEC ASA	NO0003047409	NAVAMEDIC ASA	NO0010205966
HJELLEGJERDE ASA	NO0003086902	NAVIA ASA	NO0003045007
HOFSETH BIOCARE ASA	NO0010598683	NAVIS ASA	NO0003092702
HUNTER GROUP ASA	NO0010283211	NCL HOLDING ASA	NO0003318701
HURTIGRUTEN GROUP ASA	NO0003325102	NEAS ASA	NO0010355621
HYDRALIFT ASA	NO0003031908	NEKKAR ASA	NO0003049405
ICE GROUP ASA	NO0010734742	NEL ASA	NO0010081235
IDEX BIOMETRICS ASA	NO0003070609	NERA AS	NO0003050700
IGNIS ASA	NO0003087504	NET1 INTERNATIONAL HLDGS AS	NO0010831050
IGROUP ASA	NO0003089807	NETCOM ASA	NO0003057507
IMSK SE	NO0003072803	NETCONNECT AS	NO0010445901
INCUS INVESTOR ASA	NO0003053308	NEXT BIOMETRICS GROUP AS	NO0010629108
INDUCT SOFTWARE AS	NO0010536048	NEXTGENTEL HOLDING ASA	NO0010199052
INFOSTREAM A.S	NO0003077505	NORAL ASA	NO0003398802
INFRATEK ASA	NO0010395973	NORAM DRILLING CO AS	NO0010360019
INTELECOM GROUP ASA	NO0003107609	NORBIT ASA	NO0010856511
INTELLINET ASA	NO0010036957	NORDA ASA	NO0010285190
INTEROIL EXPLORATION AS	NO0010284318	NORDIC MINING ASA	NO0010317340
ISLAND DRILLING COMPANY ASA	NO0010350564	NORDIC NANOVECTOR AS	NO0010597883
ITERA ASA	NO0010001118	NORDIC SEMICONDUCTOR	NO0003055501
IVAR HOLDING ASA	NO0003053704	NORDIC WATER SUPPLY ASA	NO0005128603
JASON SHIPPING ASA	NO0010227036	NORMAN ASA	NO0010225246
KAHOOT! AS	NO0010823131	NORPALM ASA	NO0003090607
KENOR ASA	NO0004578105	NORSE ENERGY CORP ASA	NO0003095507
KID ASA	NO0010743545	NORSK HYDRO ASA	NO0005052605
KITRON ASA	NO0003079709	NORSK LOTTERIDRIFT ASA	NO0003068306
KLAVENESS COMBINATION CARRIE	NO0010833262	NORSKE SKOG ASA	NO0010861115
KLIPPEN INVEST ASA	NO0003047805	NORSKE SKOGINDUSTRIER A/S	NO0004135633
KOMPLETT ASA	NO0010032097	NORSTAT ASA	NO0010280936
KONGSBERG AUTOMOTIVE ASA	NO0003033102	NORTH ENERGY ASA	NO0010550056
KONGSBERG GRUPPEN ASA	NO0003043309	NORWAY PELAGIC AS	NO0010373384

NORWAY ROYAL SALMON AS	NO0010331838	RIEBER & SON AS	NO0004951104
NORWAY SEAFOODS GROUP ASA	NO0010565781	ROCKSOURCE ASA	NO0003987901
NORWEGIAN AIR SHUTTLE ASA	NO0010196140	ROXAR ASA	NO0003060402
NORWEGIAN CAR CARRIERS ASA	NO0003146904	ROXAR ASA	NO0003073801
NORWEGIAN ENERGY CO AS	NO0010379266	SAFEROAD HOLDING	NO0010781743
NORWEGIAN PROPERTY AS	NO0010317811	SALMAR ASA	NO0010310956
NRC GROUP ASA	NO0003679102	SAS NORGE ASA	NO0003920019
NTS ASA	NO0004895103	SATS AS	NO0010863285
OBSERVE MEDICAL ASA	NO0010865009	SCAN GEOPHYSICAL AS	NO0010325103
OCEAN HEAVYLIFT	NO0010290786	SCANARC ASA	NO0010357338
OCEAN RIG ASA	NO0003066300	SCATEC SOLAR ASA	NO0010715139
OCEAN YIELD ASA	NO0010657448	SCHIBSTED ASA	NO0003028904
OCEANOR HOLDING ASA	NO0010097033	SE LABELS ASA	NO0010104961
OCEANTEAM ASA	NO0010317316	SEA PRODUCTION LTD	BMG8005C1047
ODFJELL SE	NO0003399909	SELF STORAGE GROUP ASA	NO0010781206
ODIM ASA	NO0010176852	SELMER ASA	NO0003049306
OFFICE LINE ASA	NO0010074396	SELVAAG BOLIG AS	NO0010612450
OFFICESHOP HOLDING ASA	NO0010070402	SENSE COMMUNICATION INTL AS	NO0010035025
OHI ASA	NO0003095408	SENSONOR ASA	NO0005379503
OKEA ASA	NO0010816895	SERODUS ASA	NO0010549801
OLAV THON EIENDOMSSELSKAP	NO0005638858	SEVAN DRILLING LTD	BMG8070J1099
ON & OFFSHORE AS	NO0010368228	SIMRAD OPTRONICS ASA	NO0005396200
ONSHORE PETROLEUM CO AS	NO0010700123	SIMTRONICS ASA	NO0010349830
OPTICOM ASA	NO0003053902	SINOCEANIC SHIPPING ASA	NO0010052350
ORKLA ASA	NO0003733800	SINVEST ASA	NO0010094519
OTELLO CORPORATION ASA	NO0010040611	SMEDVIG A/S	NO0003390205
OTOVO AS	NO0010809783	SOFTOX SOLUTIONS AS	NO0010811961
OTRUM ASA	NO0003068009	SOFTWARE INNOVATION ASA	NO0003058901
P4 RADIO HELE NORG ASA	NO0003063703	SOLON EIENDOM ASA	NO0003106700
PAN PELAGIC ASA	NO0010070634	SOLSTAD OFFSHORE ASA	NO0003080608
PANORO ENERGY ASA	NO0010564701	SOLVANG ASA	NO0003390007
PC LAN ASA	NO0010022734	SOLVTRANS ASA	NO0010566854
PCI BIOTECH HOLDING ASA	NO0010405640	SPCS-GRUPPEN ASA	NO0003057200
PETROJACK AS	NO0010244346	SPECTRUM ASA	NO0010429145
PETROMENA AS	NO0010285018	STATOIL FUEL & RETAIL ASA	NO0010584063
PGS ASA	NO0010199151	STAVANGER AFTENBLAD ASA	NO0005493601
PHILLY SHIPYARD ASA	NO0010395577	STAVDAL ASA	NO0003089302
PHOTOCURE ASA	NO0010000045	STENTO ASA	NO0003042608
PLAYSAFE HOLDING AS	NO0010306228	STEPSTONE ASA	NO0010010473
POLARIS MEDIA ASA	NO0010466022	STORM REAL ESTATE AS	NO0010360175
POLIGHT AS	NO0010341712	STRONGPOINT ASA	NO0010098247
POLIMOON ASA	NO0010263916	STX EUROPE ASA	NO0010222995
POWEL ASA	NO0003084105	SUPEROFFICE AS	NO0003054736
PROFDOC ASA	NO0003109308	SYNNOVE FINDEN ASA	NO0003073108
PRONOVA BIOPHARMA ASA	NO0010382021	TANDBERG AS	NO0005620856
PROVIDA ASA	NO0003014904	TANDBERG DATA ASA	NO0005621102
Q-FREE ASA	NO0003103103	TANDBERG STORAGE	NO0010190341
QUANTAFUEL AS	NO0010785967	TANDBERG TELEVISION ASA	NO0003070906
RAK PETROLEUM PLC	GB00BRGBL804	TARGOVAX ASA	NO0010689326
RAUFOSS ASA	NO0005257709	TEAM SHIPPING ASA	NO0003094005
RC GRUPPEN ASA	NO0003074908	TECHNOR ASA	NO0005625103
REACH SUBSEA ASA	NO0003117202	TECHSTEP ASA	NO0003095309
REC SILICON ASA	NO0010112675	TECO MARITIME ASA	NO0010176324
REC SOLAR ASA	NO0010686934	TEEKAY PETROJARL ASA	NO0010309560
REITAN NARVESEN ASA	NO0003057705	TELECAST ASA	NO0005098517
REM OFFSHORE ASA	NO0010353964	TELECOMPUTING ASA	NO0003083008
RENONORDEN ASA	NO0010723141	TELENOR ASA	NO0010063308
REPANT ASA	NO0003108508	TGS-NOPEC GEOPHYSICAL CO ASA	NO0003078800
RESERVOIR EXPLORATION TECH	NO0010277957	THE CONTAINERSHIP CO AS	NO0010566367
RICA EIENDOM ASA	NO0010154172	THIN FILM ELECTRONICS	NO0010299068

TIDE ASA	NO0003194201
TOMRA SYSTEMS A/S	NO0005668905
TORDENSKJOLD ASA	NO0003069502
TORGHATTEN ASA	NO0003427403
TREASURE ASA	NO0010763550
TROLLTECH ASA	NO0010317647
TROMS FYLKES DAMPSKIB	NO0003434003
UGLAND NORDIC SHIPPING ASA	NO0003042400
ULTIMOVACS AS	NO0010851603
UNIFIED MESSAGING SYSTEM	NO0010044225
UNITOR A/S	NO0005772004
V-VIRAL AS	NO0003109704
VEIDEKKE A/S	NO0005806802
VICTORIA EIENDOM	NO0003041402
VILLA ORGANIC AS	NO0010342900
VISMA ASA	NO0003054405
VISTIN PHARMA ASA	NO0010734122
VMETRO ASA	NO0003074601
VOICE ASA	NO0005857508
VOW ASA	NO0010708068
WALLENIUS WILHELMSEN ASA	NO0010571680
WATERFRONT SHIPPING ASA	NO0003473001
WAVEFIELD INSEIS AS	NO0010295504
WEBSTEP ASA	NO0010609662
WEGA MINING AS	NO0010324585
WEGA OIL ASA	NO0003083800
WEIFA ASA	NO0010308240
WILH WILHELMSEN HOLDING ASA	NO0010571698
WILSON ASA	NO0010252356
WINDER ASA	NO0003360307
WINTERSHALL NORGE ASA	NO0010270309
WR ENTERTAINMENT ASA	NO0010755077
XXL SPORT & VILLMARK AS	NO0010716863
YARA INTERNATIONAL ASA	NO0010208051
ZALARIS ASA	NO0010708910
ZWIPE AS	NO0010721277

[1] Notice that Gaming Innovation Group INC, Golden Close Maritime and RAK Petroleum PLC have ISINs starting with US, BMG and GB respectively. These companies are still registered as Norwegian registered foreign entities.