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How does the Norwegian stock market react to new analyst recommendations?

A study of the OSEBX from 2005 to 2020

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Preface

This thesis was written as the final part of our Master's degree at Oslo Metropolitan University. It is based on our major in Financial Economics, and constitutes 30 credits, the equivalent to one semester. We have, to the best of our abilities, attempted to put the skills and theories we have learned during our two years at Oslo Metropolitan University into this thesis.

The subject of the thesis was chosen out of a personal interest in the stock market and the effect analyst recommendations have on stocks. As both authors invest in and pay close attention to what occurs in the Norwegian stock market, the thought of writing a thesis on this subject had been on our minds for quite some time. Luckily, this interest aligns well with the subject's relevance to our major and the courses we have completed.

This thesis is the collaborative work of the authors. We are proud of the amount of time, work, and effort we have put into writing it. Our skills in *Microsoft Excel* have also greatly improved during this semester from our handling of the dataset. We believe the process of writing this thesis has given us skills and knowledge that we can take with us in our professional careers.

We would like to give special thanks to our supervisor Jacopo Bizzotto. He has been of great assistance to us this semester. His guidance and knowledge has helped us overcome the many obstacles and hurdles we faced during the thesis. We would also like to thank each other.

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Abstract

In this thesis, we have gathered and analyzed 27,669 stock recommendations on 162 different companies, issued by 44 different brokerage firms. The data analyzed is collected from 01.01.2005 to 31.12.2020, and the companies studied are the ones that have been, either briefly or throughout the whole period, part of the OSEBX index. Two event windows are applied to study both the immediate reaction and the pre- and post-event reactions. The research question we intend to answer is:

"How does the Norwegian stock market react to new analyst recommendations?: A study of the OSEBX from 2005 to 2020".

To measure the market reaction to the recommendations, we applied the guidelines presented in MacKinlay (1997). In the three-day event window, we find that the average cumulative abnormal return (ACAR) for buy, hold, and sell recommendations are 0.548%, -0.542%, and -1.060%. Hold recommendations are considered negative rather than neutral. In the 11-day event window, we find that the ACAR is positive for buy recommendations in the days before the event. However, it is negative for hold and sell recommendations, indicating a trend for the stocks before the recommendation.

Examining trading volume, we find it abnormally high in the days surrounding the issuing of the recommendation. We believe much of the increase in volume before the recommendation is caused by other events. For downgrades to sell recommendations, we believe the recommendations are the main reason for the increased volume we observe. We also explore if the number of recommendations a brokerage firm has issued during the 15 years, affects the ACAR. We find that *DNB Markets*, being the most frequent issuer of stock recommendations for the OSEBX, is the brokerage firm with the highest ACAR for both buy and sell recommendations. We believe there is a causal effect between *DNB Markets* issuing a sell recommendation and the stock yielding a negative ACAR.

Lastly, we conduct a regression analysis to distinguish some of the variables that affect the ACAR from a recommendation. The regression confirms that *DNB Markets* have a larger influence on the market than other brokerage firms. Furthermore, it shows that recommendation changes are more influential than reiterations, that a target price further away from the mean is more likely to be influential, and that a larger number of hold or sell recommendations issued on the same stock on the same day enhances the effect on the ACAR. However, the model has low explanatory power, leading us to believe more factors affect the stock price movements.

Keywords: Event Study, Abnormal Return, Abnormal Volume, Analyst, Brokerage Firm, ACAR, Stock Recommendation

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1. Introduction

1.1 Background and motivation

During our years of studying economics and finance, our interest in the stock market has increased, together with our understanding of financial theory. Both authors of this thesis are currently investing in the stock market in addition to following financial news in Norway, frequently filled with headlines of analyst recommendations, new target prices, and market predictions. We are intrigued by the fact that these often are followed up with articles claiming that “stock X” rose or fell because an analyst changed their recommendation. Hence, we want to look further into these claims regarding the effect of analyst recommendations. In this thesis, we examine the relationship between analyst recommendations and the resulting stock price movements. Are stock prices affected by analyst recommendations?

According to the semi-strong form of market efficiency, investors should not be able to profit on publicly available information such as stock recommendations (Barber et al., 2001). However, brokerage firms pour vast amounts of money and resources into stock analysis, in an attempt to persuade investors into believing that certain stocks are more attractive investments than others (Womack, 1996). Thus, market prices cannot perfectly reflect all available information, as that would make information gatherers such as analysts redundant (Grossman and Stiglitz, 1980). However, both brokerage houses and their clients must believe that the information provided by analysts can generate excess returns (Barber et al., 2001).

On average, stocks with positive analyst recommendations outperform stocks that have negative recommendations (Jegadeesh, 2004). Finance literature states that recommendation changes are associated with significant abnormal returns, though the typical estimates are often too small to be considered significant (Loh and Stulz, 2010). Thus, it is difficult for investors to distinguish the impact of a recommendation change from background noise (Loh and Stulz, 2010). Jegadeesh (2004) found that analyst recommendations may partly be driven by other incentives than the investment value of their recommendation. Analysts are normally employed at brokerage houses whose primary business focus is on other financial areas than research, such as asset management, and book-building during IPOs and subsequent offerings. This means that many of the companies covered by the research department could be customers at other departments of the brokerage house. There are rules in place to ensure the separation of the research department from the rest of the brokerage house. Still, there is a possibility that the economic incentive for the brokerage house could lead analysts, knowingly or not, to focus their attention on certain stocks (Jegadeesh, 2004).

1.2 Research Question and Structure

In this thesis, our goal is to analyze market reactions to recommendation changes. We will examine recommendations issued on all stocks that are or have been, part of the OSEBX index from 2005 to 2020. We categorize recommendation changes by their current recommendation level and the type of change that occurred. By examining volume and stock price movements during the event window surrounding the recommendation, we hope to shed light on the effect analyst recommendations have on stocks of the OSEBX index. According to *The Economist*, Oslo Børs was in 2019 the 29th largest stock exchange in the world by market capitalization (The World in Figures, 2021). Compared to other stock exchanges, Oslo Børs is heavily exposed to sectors concerning energy, shipping, and seafood. The research question that this thesis attempts to answer is:

"How does the Norwegian stock market react to new analyst recommendations?: A study of the OSEBX from 2005 to 2020".

To answer our research question, we collected end-of-day stock price and volume on all the companies included in the OSEBX index from 2005 to 2020. The data is analyzed as an event study to quantify the cumulative abnormal returns associated with the analyst recommendations. Further on, a regression analysis is used to analyze these results and uncover whether, and to what degree, certain variables surrounding the issued recommendation affect the cumulative abnormal return. We also examined the statistical significance of trading volume surrounding the event windows.

In our thesis, we make numerous findings of the impact of stock recommendations on the Norwegian stock market. We find that the average cumulative abnormal return (ACAR) is positive for buy recommendations, and negative for hold and sell recommendations. We find that there is an abnormal volume during the event window, but we can not conclude that it is because of the recommendation. Moreover, we discover that the ACAR is higher if the recommendation comes from *DNB Markets*, mostly for sell recommendations. Finally, we see in the regression analysis that recommendation changes are more influential than reiterations. Other variables affecting the ACAR are target price deviation, and the number of recommendations issued to a company on the same day.

This thesis is structured into seven chapters. Chapter one is our thesis introduction, outlining the background and motivation for the thesis, as well as our research question and structure. Chapter two focuses on the existing literature, including research papers and master theses. In addition, it contains relevant financial theory. Chapter three examines our dataset, the data collection and selection method, as well as content and data specifications. Chapter four contains descriptive statistics from the dataset, depicting interesting finds and trends from the dataset. Our Results are presented in chapter five, where we delve deeper into our findings, examine ACAR and volume surrounding the events. We also conduct a regression analysis. Chapter six will contain the discussion, structured into four sections: ACAR, Volume, Size, and the Regression Analysis. In chapter seven we will present our conclusion, highlight the weaknesses of the thesis, as well as suggesting ways to further this research.

2. Literature Review

In this chapter, we will review some similar papers and theses that influenced our work. These papers and theses are selected as we believe they have comparable properties. Loh and Stulz (2010) examine which attributes make analyst recommendations influential, while Womack (1996) in his paper finds that recommendation changes can impact stock prices. Jegadeesh (2004) found that analysts are biased to prefer so-called “glamour stocks”, meaning stocks with positive momentum, large growth, and trading volume over value stocks. From Barber et al. (2001) it is interesting to note that it is possible to create a portfolio consisting of stocks with positive recommendations and short stocks with negative recommendations to achieve an abnormal gross return. Furthermore, Frankel et al. (2006) find that the market reaction for a stock is greater on the day an analyst report is issued. Together with the financial theory listed below, this provides the theoretical framework for the thesis.

2.1 Similar Papers

When Are Analyst Recommendation Changes Influential?
By Roger K. Loh and René M. Stulz, 2010.

In their paper from 2010, Loh and Stulz investigate if, and when stock recommendations are influential. Recommendations are only classified as influential if they affect the stock price significantly. Loh and Stulz examine several different variables to uncover which traits influential recommendations have in common. The most influential recommendations are issued on small firms, with high institutional ownership, low turnover, and a lower number of prior earnings forecasts. These companies are perceived as poorly researched. Moreover, they discover that only approximately 10% of recommendation changes are influential, and so-called star analysts are more likely to be influential. In addition, analysts with previously influential recommendations are likely to be influential again, with recommendations away from the consensus being more likely to come from influential analysts.

Do Brokerage Analysts' Recommendations Have Investment Value?

By Kent L. Womack, 1996.

The article examines the ability of analysts to predict or influence stock prices. It studies a comprehensive set of recommendations from fourteen major U.S. brokerage firms from 1989 to 1991. Only the most extreme changes are analyzed, the ones added to or removed from Buy or Sell (ratings 1 and 5). The initial returns from the recommendations are large and the recommendation effect carries over for the next months, with a long post-event drift especially for sell recommendations. Further on, Womack finds that this effect is greater on stocks with smaller market caps. He concludes that analysts appear to have both stock-picking abilities and market timing.

Analyzing the Analysts: When Do Recommendations Add Value?

By: Narasimhan Jegadeesh, Joonghyuk Kim, Susan D. Krische, and Charles M. C. Lee, 2004.

In this paper, the researchers discover that analysts from sell-side firms[1] generally prefer to recommend "glamour" stocks, i.e., stocks with positive momentum, high growth, and high volume, that are relatively expensive. Their study observed the market from 1985 through 1998, with a focus on 12 variables that prior studies show have some predictive power for future returns. These variables were price momentum, earnings momentum, daily volume turnover, earnings-to-price ratio, book-to-price ratio, firm size, and growth indicators. The level of the consensus recommendation adds value only among stocks with favorable quantitative characteristics, such as value stocks and stocks with positive momentum. For stocks with unfavorable quantitative characteristics, higher consensus recommendations are associated with worse subsequent returns.

Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns.

By: Brad Barber, Reuven Lehavy, Maureen McNichols, and Brett Trueman, 2001.

This study examines whether investors can profit from publicly available stock recommendations, as academic theory and Wall Street practice are at odds regarding the issue. The semi-strong form

[1] Sell-side firms represent clients that need to raise money by selling securities. Large sell-side firms are often: investment banks, advisory firms and market makers.

of market efficiency posits that investors should not be able to trade profitably based on publicly available information, such as analyst recommendations. The goal of the paper is to estimate the abnormal returns, gross and net trading costs. These can be earned on different investing strategies designed to take advantage of analyst stock recommendations. The researchers found that from 1986 to 1996, a portfolio of the stocks with the most (least) favorable consensus analyst recommendations, provides an average annual abnormal gross return of 4,13 (-4,91) percent, after controlling for market risk, size, book-to-market, and price momentum effects. To achieve this gross return, it was necessary to rebalance the portfolio daily. However, the transaction costs from this rebalancing diminished the returns and reduced the ability to profit from the strategy.

Determinants of the Informativeness of Analyst Research.
By: Richard Frankel, S.P. Kothari, and Joseph Weber, 2006.

The article examines the effect analyst reports have on security prices. On average, analyst reports are informative, and the market reaction on the days of issued reports is greater than on other days. The number of analysts covering a firm does not seem to diminish the estimated effect from these reports.

2.2 Similar theses

Does the Market Trust Analysts?: An Empirical Study of Analyst Recommendations Influence on the Stock Market.
By: Ole-Martin Goksøyr and Lars Andreas Grønn, 2019.

This thesis studies individual stock recommendations for 25 companies on Oslo Børs in the period 2007-2018. Goksøyr and Grønn look at the 25 companies included in the OBX index by the end of their research period. They only look at recommendations from the top 21 brokerage firms. The authors conclude that buy recommendations yield small positive abnormal returns, while hold and sell recommendations yield small negative returns. All results are significant on the 1% level.

Gosøyr and Grønn attempt to identify characteristics of the recommendations that have the highest abnormal returns and find that recommendations away from the consensus are more likely to affect the stock price. They discover that their model has little explanatory power and that recommendations to a small degree are the cause of abnormal returns. The thesis is in many ways similar to ours, however, it is smaller in scope. The number of companies, brokerage firms, and the time period is smaller than what is examined in our thesis.

2.3 Theory

2.3.1 Analysts and Recommendations

Stock recommendations are normally issued by analysts employed at brokerage firms. The analysts make forecasts of the cash flows and market conditions for the companies they follow. Based on these forecasts, the analysts provide the customers of the brokerage firm with investment recommendations. In his 1996 paper, Womack states that brokerage firms invest massively in gathering, analyzing, and publishing research and recommendations. Yet, most recommendations do not lead to abnormal returns for investors. However, as we will show in this thesis, some recommendation changes appear to lead to higher trading volume and an abnormal return.

Womack (1996) has some interesting findings regarding the characteristics of companies given buy or sell recommendations. He found that at the time companies were added to the buy-list, their median P/E ratio[2] was 12.5, while at the time they were removed from the buy-list their P/E ratio was 13.0. The same tendency was found for the Price/Book ratio; less expensive companies are more likely to be added to the buy-list and more expensive ones are likely to be removed from the same list. Womack concludes that most recommendations are based on public information and not private information.

[2] The price-to-earnings ratio (P/E ratio) is a measurement for valuing a company. It measures the company's price per share relative to its earnings per share (EPS).

Sell recommendations are less common than buy recommendations and buy recommendations occur almost seven times more often than sell recommendations (Womack, 1996). Barber et al. (2001) finds that only 5.7% of their observations are sell recommendations compared to 47.1% buy observations.

The firms employing analysts are commonly full-service financial companies, with their most profitable contracts generally within the investment-banking segment. Maintaining good relationships with current and future clients is important to secure future business relations. According to Womack (1996), analysts are well aware that there could be substantial costs or risks linked with issuing sell recommendations. Pratt (1993) mentions two important potential costs of issuing negative recommendations. The first is harming the relationship between the investment bankers and their current and future customers. Issuing negative recommendations is therefore discouraged by investment bankers. The second is that top management and investment contacts may cut off or limit the flow of information to analysts issuing unfavorable reports.

Analysts are employees working for a salary. The structure of their compensation is therefore considered an important factor in understanding the incentives behind a recommendation. These incentives may be financial, reputational, or based on loyalty and will differ between organizations and individuals. Looking at the largest private investment bank in Scandinavia, ABG Sundal Colliers 2020 annual report we can see that the “Brokerage and Research” department accounted for 26% of the revenue. A fair amount of this revenue is made from the 100 companies that are now part of the “sponsored research franchise”, where companies pay for analyst coverage. We choose not to dig deeper into the independence of analysts, but it can be questioned.

Jegadeesh et al. (2004) point out that most prior studies conclude that information provided by analysts promotes market efficiency, by helping investors more accurately value companies. Thus, in the next section we will present the market efficiency hypothesis.

2.3.2 Market Efficiency Hypothesis

The efficient market hypothesis was introduced by Eugene Fama in 1970 and has been a cornerstone in financial theory since. Fama argued that beating the market over time is impossible since all information is reflected in the share prices. Thus, alpha generation for investors will, over time, be impossible. The theory can be broken down to the degree of information that is reflected in share prices and sorted into three categories (Bøhren et al., 2017).

- <u>Weak form:</u> Share prices reflect all information in market data, including price history and volume. Therefore, technical analysis can not be used to beat the market.
- <u>Semi-strong form:</u> Share prices reflect market data and all public information. This includes earnings reports, budgets, and public plans. In this form, fundamental or technical analysis can not be used to beat the market.
- <u>Strong-form:</u> All information, private and public, is reflected in stock prices. Only luck can lead to beating the market.

Despite the high regard in which this theory stands, it has received its fair share of criticism. Events such as asset bubbles and market crashes are mentioned when arguing that asset prices can seriously deviate from their fair values. There are also numerous examples of investors who have beaten the market year after year, which according to the EMH is impossible.

2.3.3 Measuring Abnormal Returns

The abnormal return is the actual return of the stock during the event window minus the normal return of the stock during the estimation window (MacKinlay, 1997). Calculating the abnormal return is necessary to find the effect of a recommendation change on the stock price. The formula for calculating the abnormal return ($AR_{i\tau}$) for firm i in the event period τ is shown below:

$$AR_{i\tau} = R_{i\tau} - E(R_{i\tau}|X_\tau).$$

Where $R_{i\tau}$is the actual return and $E(R_{i\tau}|X_\tau)$is the normal return. $X_\tau$is the conditioning information for the normal return and there are two common ways to model this. In this thesis the market model is applied, where X_τ is the market return[3]. The market model assumes a stable linear relationship between the market return and the stock return. (MacKinlay, 1997)

The abnormal returns must be aggregated to observe the development during the event window. The Cumulative Abnormal Return (CAR) is the sum of the abnormal returns in the event window.

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau}.$$

To find the Average Cumulative Abnormal Return (ACAR) the sum of all the CAR´s must be divided by the number of events. This is shown in the formula below.

$$ACAR = \frac{1}{N}\sum_{i=1}^{N} CAR_i.$$

2.3.4 The Market Model

The market model is a statistical model which links the return of a given stock to the return of the market portfolio. The model assumes that asset returns are jointly multivariate normal, independent, and identically distributed over time. With these assumptions, the disturbance term is Gaussian white noise. This implies that the disturbance term has an expected value of zero, homoscedasticity[4] and no autocorrelation[5]. For any stock i the market model formula is:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \varepsilon_{it}.$$

Where $R_{it}$is the arithmetic return of stock *i* in period *t*. $R_{mt}$is the return of the market portfolio in period *t*. A broad index should be used as the market portfolio, for example the S&P 500 or in our case, the OSEBX. $\beta_i$is the parameter for how much the market return affects the stock return. $\varepsilon_{it}$is the models disturbance term and $\alpha_i$is the stock's return beyond the market return. The benefit of using the market model will depend on the $R^2$of the model´s regression. “The higher it is, the

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[3] The other method is the constant mean return model, where X is a constant. The constant mean return model assumes that the mean return of a given stock is constant through time. (MacKinlay, 1997).

[4] Homo means “same” and scedasticity means “variance”. Homoscedasticity means that the variance of the error terms should be the same, regardless of the value of the other variables.

[5] Autocorrelation (also known as serial correlation), is the degree of correlation of a variable between two successive time intervals.

greater is the variance reduction of the abnormal return, and the larger is the gain" (MacKinlay, 1997).

Further on, MacKinlay (1997) discusses the possibility of using different factor models in event studies. However, he concludes that the gains from using multifactor models are limited. He specifically argues against using the Capital Asset Pricing Model. Based on this, the analysis in this thesis will be conducted using only the one-factor market model.

2.3.5 Measuring Abnormal Volume

When measuring the abnormal volume, the same principle as for measuring the abnormal returns is followed. An estimation window of 125 trading days is used to establish what the average volume has been in the period leading up to the recommendation. The following equation is applied:

$$AV_{it} = \frac{V_{it}}{\sum_{t=-6}^{-125} V_{it} \times \frac{1}{125}}.$$

2.3.6 Event window and Estimation window

The event window is the period over which the prices of a stock involved in an event will be examined. The event window should always be larger than the period of the specific event, as some may get their hands on information regarding the event sooner than others. The event window itself should not be included in the estimation window to prevent it from influencing the estimates.

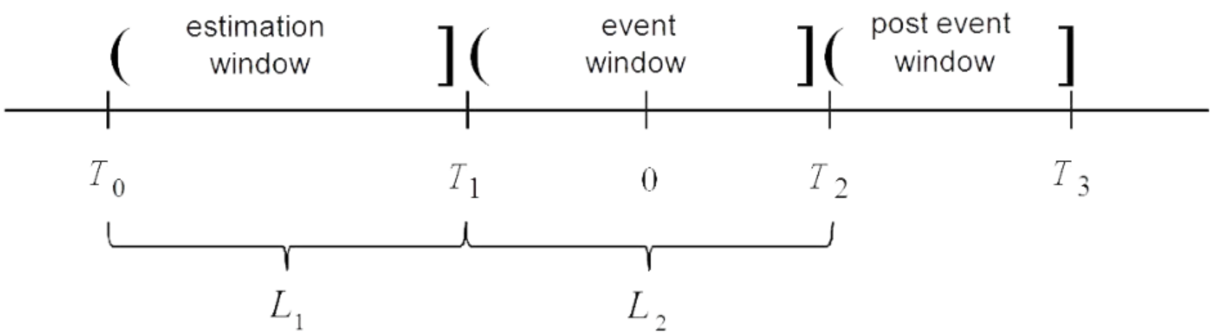

Figure 2.a: Showing on a timeline, how estimation and event windows should be set up. From MacKinlay (1997).

In his article, MacKinlay (1997) uses a 41-day event window, comprising the 20 trading days before the event day, and the 20 trading days after. The estimation window is set to the 250 trading days before the start of the event window. Womack (1996) uses one day before and after to measure the immediate reaction.

For this thesis, it is assumed that the OSEBX has semi-strong efficiency. In other words, it takes some time for investors to react to news, and it would be reasonable to expand the event window to include more than just the event day. Another reason for doing this is that the dataset includes recommendations from international brokerage firms. The exact time of day these recommendations are issued is uncertain.

Based on what is mentioned above, this thesis will apply two event windows. One to measure the immediate reaction, and another to capture some of the pre- or post-event drifts. These are set to three and eleven days, which is L_2in Figure 2.a. The estimation window, L_1in Figure 2.a, is set to 125 days before the event window. This estimation window is shorter than what MacKinlay (1997) uses, but so are the event windows.

2.3.7 R^2(Goodness of Fit)

R^2or R-squared is the ratio of explained variation compared to the total variation. In other words, it is interpreted as the fraction of the sample variation in y that is explained by x or simply; how well x explains y. It is a measurement of how well the OLS regression line fits the data. The R-squared of the regression also goes by the name coefficient of determination. This can be computed with the following formula:

$$R^2 = SSE/SST = 1 - SSR/SST.$$

Where SST is the total sum of squares, SSE is the explained sum of squares and SSR is the residual sum of squares. The value will be between 0 and 1, where a higher value is better (Wooldrigde, 2013).

2.3.8 T-test

In most t-tests, the goal is to observe if one variable (for example education) has a causal effect on another variable (for example wages). For education to have causality (cause and effect) on wages, it must be partly responsible for the size of the wages and the wages have to be partly dependent on education. In our tests, we want to see if recommendations affect stock prices and trading volume.

The formula for our t-test is:

$$t = \frac{ACAR}{\sqrt{Var(CAR)}}.$$

Where:

$$\sqrt{Var(CAR)} = \frac{1}{N^2}\sum_{i=1}^{N}(CAR_i - ACAR)^2,$$

and the hypotheses are:

$$H_0: t = 0.$$

$$H_1: t \neq 0.$$

The t-test gives a t-value that tells whether we can reject the null hypothesis or not. Depending on the level of the p-value, the results are significant or not. The three most common levels used to determine significance are at the 90%, 95%, or 99% confidence interval. At 90%, the p-value for a two-tailed t-test needs to be below 0,1. For 95% it is 0,05 and for 99% it is below 0,01. The t-value contains similar information and must be above 1,645, 1,96, and 2,58 for the respective confidence intervals to yield significant results where the null hypothesis is rejected. The rejection of the null hypothesis means that there is a significant difference between the samples examined, that can not be explained by chance.

3. Data

3.1 Defining the Event

The first step when conducting an event study is to define the event you want to study (MacKinlay, 1997). In this thesis, we will explore how different recommendations affect the stock price and volume of companies included in the OSEBX index. All companies that have been part of the index, either briefly or through the whole period, from 2005 to 2020, will be included. We believe it necessary to include stocks that have been removed from the index or delisted, to reduce the effect of survivorship bias[6]. Each recommendation is defined as one event, and we will therefore have thousands of event-observations. Each observation contains the following information:

- Company ticker;
- The date the recommendation is issued;
- The name of the brokerage firm issuing the recommendation;
- A recommendation on a scale from 1 to 3, where 1 is a buy, 2 is hold, and 3 is sell;
- The mean of all recommendations that are valid at this date, on a scale from 1 to 3;

[6] Survivorship bias is the logical error of focusing on the stocks who have made it and not the ones who have failed. This can lead to false conclusions and making results seem better than they are.

- The target price accompanying the recommendation issued by the analyst. Represents the analysts estimated value of the share;
- The mean of all issued target prices that are valid at this date for the stock;
- Deviation from target price mean. Shown in percentage, how far the target price deviates from the mean;
- The previous recommendation. Shows the previous recommendation issued by this broker;

3.2 Gathering and structuring the Data

The dataset is the foundation of our thesis, and all further analysis will be built upon it. It is therefore of importance that the data collected is as correct and complete as possible. *Refinitiv Eikon* is a financial software that contains vast amounts of financial data on companies and financial markets around the world, including the I/B/E/S[7] Estimates system. This tool was instrumental in the data collection process, as it removed the need to contact the different brokerage firms to obtain the data. It contained the necessary information of which stocks had joined and left the OSEBX index during the time period, their end of day price information, trading volume and issued recommendations. This data was downloaded, sorted, and prepared for manual cleaning in *Microsoft Excel*. *Microsoft Excel* was used throughout the entire process, and it was here our models and analyses were constructed.

3.3 Price Data

The individual stock price data was collected using *Eikon Datastream*. It is represented as the closing price of each trading day, and the prices are adjusted for any dividends, stock splits or reverse splits that may have happened. If stock prices are not adjusted, the price will, according to theory, drop by the same amount as the dividend being distributed. On the ex-dividend date, the stock price will normally drop several percent, but in reality, the investors have cash coming their way. Adjusted prices are therefore used to avoid these events affecting the daily returns.

[7] Institutional Brokers Estimate System.

3.4 Time period

To have sufficient data on brokerage firms and stocks, a relatively long time period was chosen. The 15-year period from 2005 to 2020 is the period that will be studied. The long time period ensures that our dataset contains both recessions and periods of high economic growth, as well as short term crashes and quick rebounds. This will allow us to see if there are certain periods where analysts are more influential and active than others.

3.5 Brokerage firms

A total of 127 different brokerage firms that had issued recommendations on the stocks from the OSEBX index during 2005-2020 were found. Many the recommendations were issued by brokerage firms we could not see the name of. These firms were identified by "Permission denied" and a specific numeric code. For example, "Permission Denied 170800". This does not affect the data, as the identifiers are linked to the recommendation issuers throughout the dataset.

In the top 15 most active brokerage firms, we have six anonymous brokers. We have not tried to identify each of them, however, we note that some of the large brokers missing from our list are: *ABG Sundal Collier, Kepler Cheuvreux, Nordea Markets*, and *Sparebank 1 Markets*. The brokerage firms *Carnegie, Handelsbanken,* and *UBS* had no available stock recommendation data in *Eikon* and are not included in our dataset. These three would presumably rank in the top 15 shown in Table 3.a, had their data been available.

Brokerage Firm	Buy	Hold	Sell	Total
DNB Markets	1 584	762	440	2 786
Norne Securities	1 067	600	308	1 975
Anonymous 1	1 183	341	326	1 850
Anonymous 2	1 073	461	162	1 696
SEB Equities	897	417	184	1 498
Arctic Securities	938	419	118	1 475
Anonymous 3	848	387	203	1 438
Pareto Securities	923	417	71	1 411
Anonymous 4	832	438	104	1 374
FIRST Securities	822	394	155	1 371
Anonymous 5	396	489	200	1 085
Fearnley Securities	605	43	276	924
Swedbank Markets	428	284	91	803
Clarksons Platou Securities	401	223	87	711
Anonymous 6	278	202	191	671

Table 3.a: Showing the top 15 brokerage firms, based on the number of total recommendations.

DNB Markets is the brokerage firm that has issued the most stock recommendations during the time period. This is to be expected, as they have been the largest brokerage firm in Norway in our time period[8] (Oslo Børs, 2008). From the table above it is also clear that *Pareto Securities* is issuing the fewest sell recommendations out of the top 15 brokerage firms. Only 5.03% of *Pareto´s* recommendations are sell. *Fearnley Securities* on the other hand, is the company issuing the fewest hold recommendations. Only 4.65% of their total issued recommendations are hold.

3.6 Companies

We found that there were 167 companies that at some point, had been included in the Oslo Stock Exchange Benchmark Index (OSEBX) from 2005 to 2020. The OSEBX constitutes the largest and most traded shares listed on Oslo Børs. It is in Norwegian referred to as “Hovedindeksen” (The Main Index). This index is a representation of the development of the Norwegian stock exchange. The index is semiannually revised, and per 31.03.2021 it is made up of 69 companies (Euronext, 2021). It was chosen for this thesis as it contains a large sample of companies with different characteristics:

[8] Data was only available back to 2008.

- Companies with large and small market capitalizations;
- Different range of sectors;
- High and low growth rates;
- Positive and negative earnings;
- Different levels of analyst coverage;

Company	Buy	Hold	Sell	Total
EQNR	585	439	218	1 242
YAR	464	395	147	1 006
TEL	583	315	96	994
DNB	514	331	91	936
SUBC	527	235	173	935
NHY	443	305	151	899
AKERBP	478	243	38	759
PGS	414	185	140	739
SDRL	290	253	177	720
MOWI	339	217	134	690
AKAS	308	209	126	643
TGS	258	183	172	613
DDASA	238	207	134	579
REC	282	146	144	572
SBSTA	320	178	70	568

Table 3.b: Showing the top 15 companies, sorted by the number of total recommendations.

From the table above we see that seven of the top 15 companies operate in the oil and gas sector. Equinor, Yara, DNB, Telenor, Subsea 7, and Norsk Hydro are the companies that have received the most recommendations during the time period. They have been listed on the exchange throughout 2005-2020, and as companies with market caps in the billions of dollars, this unsurprisingly leads to a high rate of coverage from brokerage firms.

3.7 Data Filtering and Conflicting Events

During the structuring of the data, it was necessary to filter away certain events, mend data points, and remove clearly erroneous data. First, the data from Eikon was manually cleaned up, as the dataset had several flaws. An error we often encountered was where an ongoing recommendation and its target price suddenly dropped to zero, and then returned to the previous levels the following day. This had to be mended as it was necessary to ensure that one recommendation would not be registered as two in the later analysis. We also removed recommendations that were incomplete, missing either the recommendation level or the target price. There were some recommendations that had fluctuating target prices, which we believe were linked to currency movements. This would result in very small daily changes to the target price that made it difficult to observe where the actual recommendation change occurred. When uncertain if it was an actual recommendation or a currency change, the recommendations would be removed. Where this was clearer, we wrote over the daily changes with the initial target price until an actual new recommendation change was observed.

This left us with a total of 38 163 recommendations. Further on, we decided to drop recommendations from brokerage firms that had issued 50 or fewer recommendations during the 15 years we were examining. It is our belief that these recommendations were so scarce and infrequent that their influence would be minimal. This led to the removal of 83 brokerage firms, who had issued a total of 925 recommendations. 44 brokerage firms were left[9].

Earnings releases are quarterly events where a company presents their results from the previous quarter. We do as Frankel et al. (2006) and remove recommendations that are issued in connection with quarterly events. Earnings releases are linked to greater return volatility (Beaver, 1968), and it would be difficult to separate their effects on the stock price movement from the effect of the recommendations. This led us to remove recommendations issued on the day of earnings releases, as well as those issued the day before and after. We were then left with 29 643 recommendations. This means we removed approximately 20.4% of the recommendations because they were issued

[9] Full list in Appendix 9.2.

around earnings releases. This is large compared to Loh (2010), who finds the equivalent to be around 13% for US stocks.

Finally, we once again filtered away recommendations that still either had missing data or contained extreme, unexplainable values. After this process, five companies[10] had zero recommendations during the period, leaving 162 different companies in our dataset[11]. In the end we were left with a total of 27 669 recommendations that we used in our analysis. An important factor to note is that the analysis uses a calculated expected return based on a stock's price movement the previous 125 trading days. This leads to recommendations issued during the 125 first trading days of 2005 being ineligible, and therefore removed.

3.8 Clustering

In our analysis, we have event windows that overlap but we do not have overlapping event dates. In a perfect analysis, it would be normal to assume that the event windows do not overlap in calendar time. This would allow us to calculate the variances without concern about the covariances. When the event windows overlap and the covariances are not zero, we get clustering (MacKinley, 1997).

Brown and Warner (1985) show that results do not have to be radically different when there is clustering in event dates. We therefore chose not to remove recommendations that are issued on days with more than one recommendation on the same company. The reason for keeping those recommendations as well as overlapping recommendations is that we fear we may miss some important data if they are removed. When our event windows are 11 days long, we have several event windows overlapping in the dataset, so it would be difficult to decide which recommendations to remove.

[10] Fjord1, Origio, Teekay Petrojarl, Morpol, REC Solar.
[11] Full list in Appendix 9.3.

4. Descriptive Statistics

In the following chapter, we will examine our dataset through descriptive statistics. We will first break down the number of active analysts and recommendations that are issued for each year of our time period. Second, we will examine the direction of recommendation changes and which type of changes are the most common. In the following section, we will present how the target prices for the different recommendations deviate from the mean. Then, we will examine the CAR for the different recommendations and the number of positive and negative outcomes. After this, we will present the average abnormal volume in the long event window. Finally, we will discuss the similarities and differences between our data, and the data of other studies.

4.1 Time

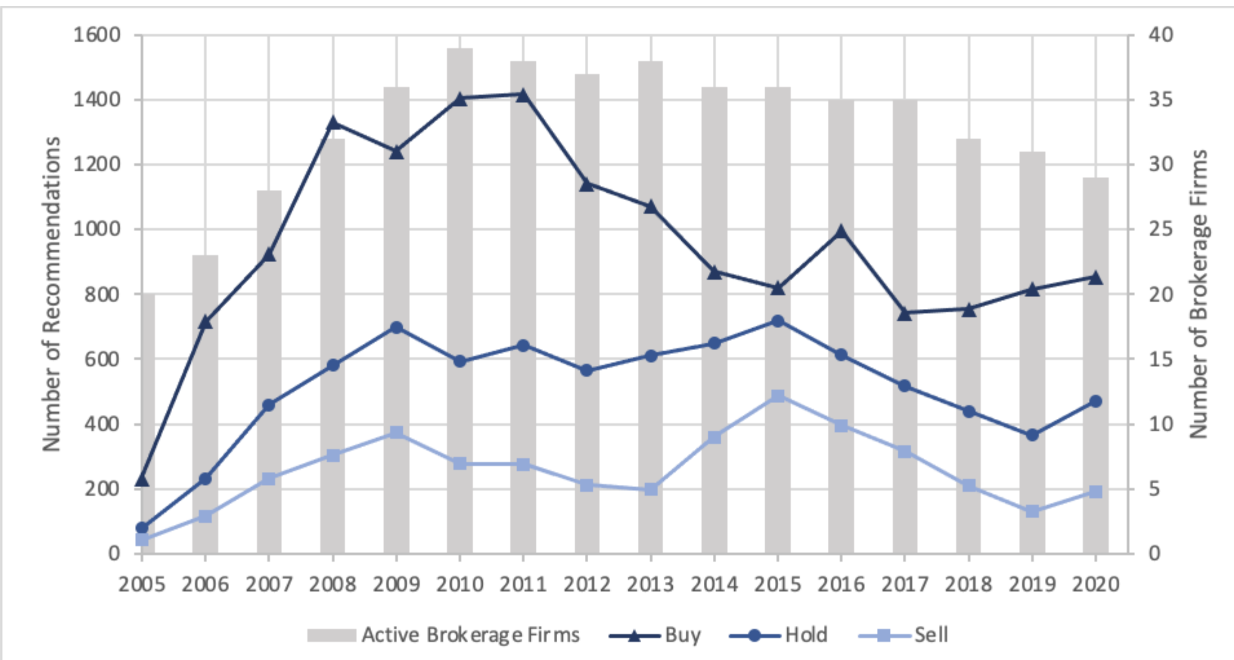

Figure 4.a: The number of active analysts per year, with the number of recommendations issued each year by type.

By including all companies that have been part of the OSEBX index, one might expect there to be the same number of active brokerage firms and issued recommendations each year. However, from Figure 4.a, these numbers vary greatly from year to year. In this section, possible explanations for the variations will be presented.

For the year 2005, as mentioned in chapter 3.7, we only have recommendations for the second half of the year. This is the reason for the low number of active analysts and total recommendations. After removing brokerage firms with less than 50 recommendations in total, we may have removed one or more brokerage firms that went out of business during the financial crisis that hit in 2007-2008, This may explain why there were so few active analysts in 2006. *Lehman Brothers* is the only firm left in our dataset that went bankrupt in 2008, but there has been no research conducted on the 83 brokerage firms that were removed.

From the dataset, we observe that some of the companies that are very active today were not issuing recommendations in the first years of our dataset. This includes *Berenberg, Clarksons Platou, Swedbank Markets, Pareto Securities, SEB,* and *First Securities*. These companies were all founded before the year 2000 but became active in our sample between 2006-2010. We also know of two companies that contribute with a lot of recommendations that were founded in 2007 (*Arctic Securities*) and 2008 (*Norne Securities*). The companies mentioned in this part, contribute to the increase we observe in active brokerage firms from 2005 to 2010.

From Figure 4.a, a clear trend is observed: the number of active analysts and total recommendations decreases steadily from their peak around 2010. Of the ten companies that stopped issuing recommendations after 2010, we found the names on nine of them. After some research, we discovered that five of them were foreign investment banks that apparently cut their coverage of the Norwegian market. This is assumed as all five are still operating today. One company was shut down by Finanstilsynet (Financial Supervisory Authority), for misconduct. The final three were part of mergers or acquisitions.

The number of buy recommendations decreased to a low in 2015, where hold and sell recommendations peak. The beginning of this decline could probably be somewhat related to the European debt-crisis that unfolded in this period. The end of the decline, on the other hand, can be explained by the massive drop in oil prices that saw the price per barrel go from $112 in June of 2014 to $31 in January 2016 (Pest, 2018). Many of the companies listed on Oslo Børs operate in the oil-industry and this sector was in severe distress at the time. Sell recommendations increased a lot and peaked in 2015, the height of the oil-crisis. The spike in Buy recommendations in 2016 can also be seen in context to this event as the companies affected were oversold and in 2016 the oil market started to recover.

4.2 The Direction of Recommendation Changes

After viewing the number of recommendations issued and their distribution over the 15-year period, the data will be explored from a different angle. The direction of the recommendation changes. It is interesting to see the discrepancy between the recommendation types in numbers issued. Examining the changes brokerage firms make to their recommendations over time allows us to better understand the data and how analysts operate.

Changes in recommendations		Recommendation at time t			
		Buy	Hold	Sell	Total
Recommendation at time t-1	Buy	11 996	2 235	425	**14 656**
	Hold	2 015	4 893	906	**7 814**
	Sell	442	825	2 601	**3 868**
	No rec	871	277	183	**1 331**
	Total	**15 324**	**8 230**	**4 115**	**27 669**

Table 4.b: Changes in recommendations from time t-1 to time t.

Table 4.b depicts the changes in recommendations from time t-1 to time t. The table contains information on how many recommendations have been reiterated and how many have received changes. The reality is, most of the recommendations issued are reiterations, and actual up or downgrades are less common. A total of 19,490 of the 27,669 recommendations are reiterations, representing 70.4% of all the recommendations issued. It is also interesting how rarely analysts

will change a recommendation from a buy to a sell, and vice versa, with these recommendation changes only making up a small 3% of all the recommendations issued combined. The table shows that the upgrade of hold recommendations to buy recommendations is more than twice as frequent as downgrades to sell. This is in line with previous findings of the reluctance of brokerage firms to issue negative recommendations (Womack, 1996). In percentages, this becomes even more evident.

Changes in recommendations %		Recommendation at time t			
		Buy	Hold	Sell	Total
Recommendation at time t-1	Buy	43,4 %	8,1 %	1,5 %	**53,0 %**
	Hold	7,3 %	17,7 %	3,3 %	**28,2 %**
	Sell	1,6 %	3,0 %	9,4 %	**14,0 %**
	No rec	3,1 %	1,0 %	0,7 %	**4,8 %**
	Total	**55,4 %**	**29,7 %**	**14,9 %**	**100,0 %**

Table 4.c: Direction of recommendation changes in percentages.

Recommendations issued by analysts consist of both a recommendation type, such as buy, hold, or sell, and a target price. Examining the recommendation types only gives half the picture, and it is therefore of interest to observe the changes in target price as well. Table 4.d shows how many of the recommendations receive an upgraded, downgraded, or unchanged target price. They are relatively evenly divided between upgrades and downgrades, with a smaller number of recommendations with unchanged target prices. The 1,644 recommendations with target prices are from when analysts change the recommendation type and reiterate the previous target price. As Table 4.d shows, it is far more common for analysts to adjust the target price than not, and this partially explains the high amount of recommendation reiterations.

Changes in target price	Upgraded	Unchanged	Downgraded	Total
Buy	7 669	700	5 805	**14 174**
Hold	3 587	647	3 598	**7 832**
Sell	1 416	297	2 166	**3 879**
First rec				**1 784**
Total	**12 672**	**1 644**	**11 569**	**27 669**

Table 4.d: Direction of target price changes when a new recommendation is issued.

4.3 Target Price Deviation

The dataset also contains information about the mean target price at the time of the issued recommendation. The target price deviation is the difference between the target price accompanying the recommendation and the mean target price at the time. The mean target price is the average of all outstanding target prices. If only one analyst is covering a stock, the deviation will always be zero.

Table 4.e shows in percentage how many of the buy, hold, and sell recommendations were issued with a target price below and above the mean. Buy and hold recommendations mirror each other, with 68% of buy recommendations being issued with target prices above the current mean. For hold recommendations, 68% of target prices are below the mean. For sell recommendations, the share is greater, with 91% of recommendations issued with a target price below the mean.

Target price from mean	Below mean	Above mean
Buy recommendations	32 %	68 %
Hold recommendations	68 %	32 %
Sell recommendations	91 %	9 %

Table 4.e: Distribution of recommendations with target prices below or above the mean.

In Figure 4.f, the target price deviations for each recommendation type is presented in more detail. Hold recommendation deviations closely resemble the normal distribution curve. Most of these recommendations come with a target price close to the consensus. However, there is an overweight of observations with a target price lower than the mean.

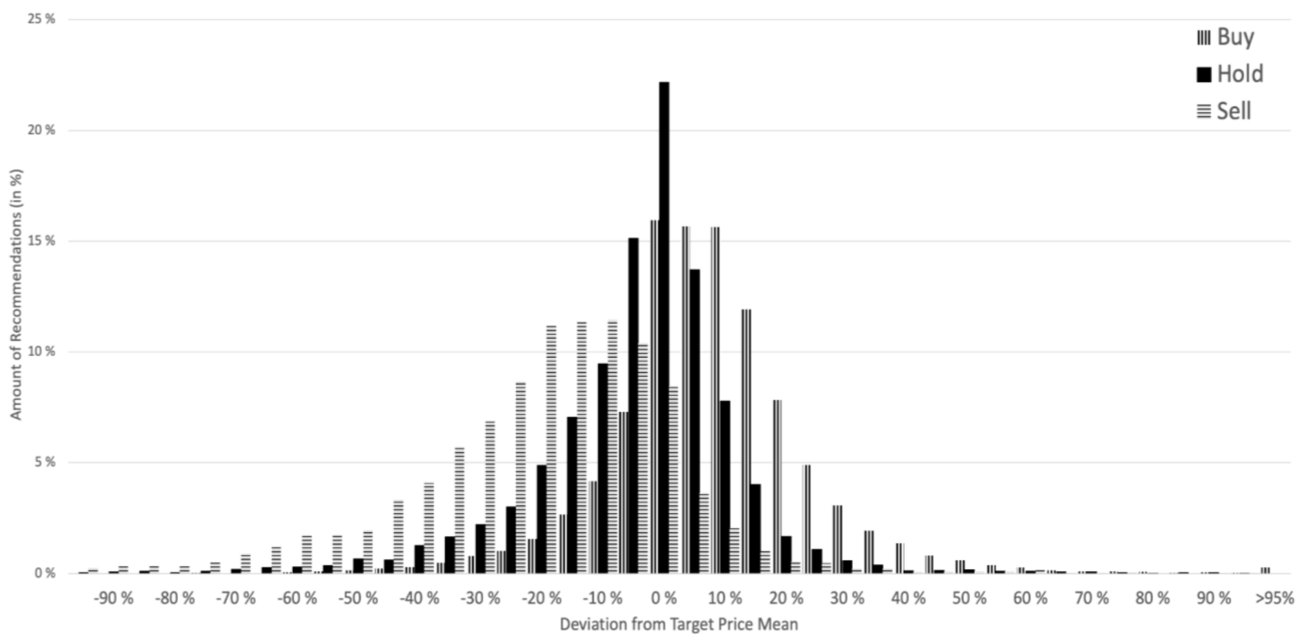

Figure 4.f: The distribution of Target Price Deviations for the different recommendation categories.

Sell recommendations are, as established in table 4.e, and shown in Figure 4.f, most often accompanied with a target price that is below the mean. The tallest bars are between -10% and -20%, but there are also a significant number of sell observations with deviations lower than -50%. The deviations for buy recommendations are expected to be positive, and they mostly are. Almost 50% of the recommendations have a target price deviation between 0% and 10%. Few, but some buy observations have target prices below the mean. There is also a small number of deviations that are over 95% above the mean.

4.4 Direction of CAR

[-5,5]	Positive	Negative
Buy	8088	7236
Hold	3838	4392
Sell	1777	2338
All	13703	13966

[-1,1]	Positive	Negative
Buy	8218	7106
Hold	3667	4563
Sell	1707	2408
All	13592	14077

Table 4.g: Direction of CAR for the different recommendations. Showing both event windows.

Table 4.g shows how many of the recommendations lead to positive and negative CAR for both the event windows. Unsurprisingly, we see that most sell recommendations lead to a negative CAR, while most buy recommendations lead to a positive CAR. There is a higher number of buy recommendations that lead to a positive CAR, and a higher number of hold and sell recommendations that lead to a negative CAR, in the short event window.

It is important to note that for both event windows hold recommendations lead to a negative CAR. Meaning that investors appear to view hold recommendations as a negative event. This is interesting, as the market reaction to a recommendation can tell us something about how a certain type of recommendation is perceived by the market. With hold recommendations being neutral by nature, it would be assumed that the market reaction also would be neutral. As we will show further on in this thesis, this is seemingly not the case, with hold recommendations being perceived negatively by the market.

4.5 The Effects on Volume

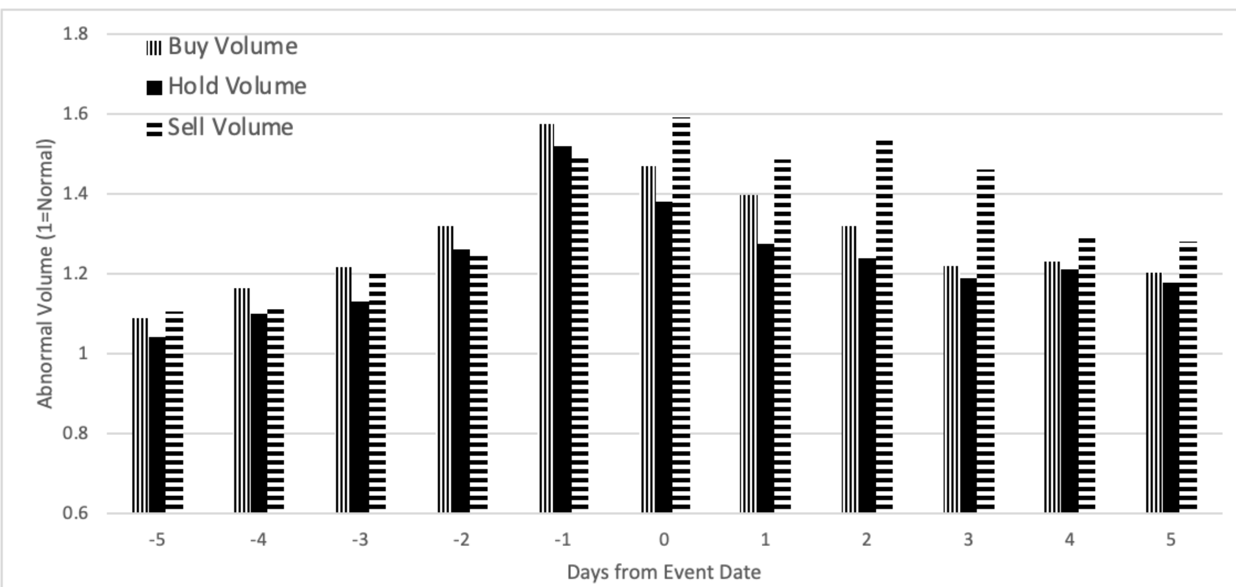

Figure 4.h: Showing the Average Abnormal Volume for all Recommendations.

In this section, we will look at the effects on volume. Figure 4.h shows the average abnormal volume for all buy, hold, and sell recommendations during the event window. The volume in the event windows is higher than its average in the 125 trading days before. The extent of the increase, however, appears to depend on the type of recommendation. For hold recommendations, the effect appears to be the lowest. Interestingly, for buy and hold recommendations, the volume peaks the day before the recommendation is issued.

For the sell recommendations, the abnormal volume peaks on the event date. This indicates that the market is affected by these recommendations. Contrary to the two others, sell recommendations appear to have a more lasting effect on the volume. The volume on days one, two, and three after the event are much higher than normal, and higher than for buy and sell recommendations. This indicates that the market is more likely to take notice and act upon sell recommendations, than other recommendations. With these descriptive statistics examined, the analysis will be conducted in chapter 5.

4.6 Studies with Similar Data

We find approximately 3.7 times more buy recommendations than sell. For the period 89-91, Womack (1996) finds for the American market, the ratio is almost 7 to 1. Pratt (1993) estimates that his dataset has a ratio of 10 to 1. However, from Figure 4.a we see that this ratio varies in our sample from year to year. From this figure, we calculate that the highest ratio we have is 6.3 while the lowest is 1.7.

The similarities in the data between Womack (1996) and us, is that both examine stocks included in a large index and that we exclude brokerage firms that are small. However, Womack (1996) only includes the 14 largest brokers, while this thesis includes recommendations from the largest 44. The price-to-earnings ratio, and market capitalization of stocks, as well as the size of the brokerage firms in the sample, might be a determining factor when comparing the magnitude of the ACAR and abnormal volume. Another difference is that Womack (1996) only studies data from a two-year period, while we have a 15-year period. As we will show in chapter 5.3, in our sample the ACAR differs greatly from year to year.

Goksøyr and Grønn (2019) conducts their thesis on the OBX which consists of the top 25 most liquid stocks, using a similar time period as this thesis. This, in addition to restricting the number of brokers to the top 21, may explain the differences in our results. However, they use the same (-1,1) event window as us and are thus a natural comparison. Goksøyr and Grønn (2019) have a higher amount of reiterations in both recommendations and target prices than us. The most distinct difference is for changes in target prices, where 59% are unchanged, compared to only 5.9% in our sample. For reiterated recommendations, the amount is 91.7% versus 70.4%.

5. Analysis

In this chapter, we present the results of the analysis. First, we will examine the ACAR for the different types of recommendations. Further on, we will study recommendations upgraded to buy and downgraded to sell more closely. Abnormal volume findings will be presented, as well as ACAR. Next, the ACAR will be studied year by year and compared to the annual returns of the OSEBX. Finally, we will examine if the size of the brokerage firms matters for the observed ACAR.

5.1 ACAR in the Event Windows

In this section, the ACAR for the three different recommendations will be displayed. We will consider both recommendation changes and recommendation reiterations. We include upgrades and reiterations in the buy category. In the hold category we include upgrades, downgrades, and reiterations. The sell category contains downgrades and reiterations.

5.1.1 Short Event Window

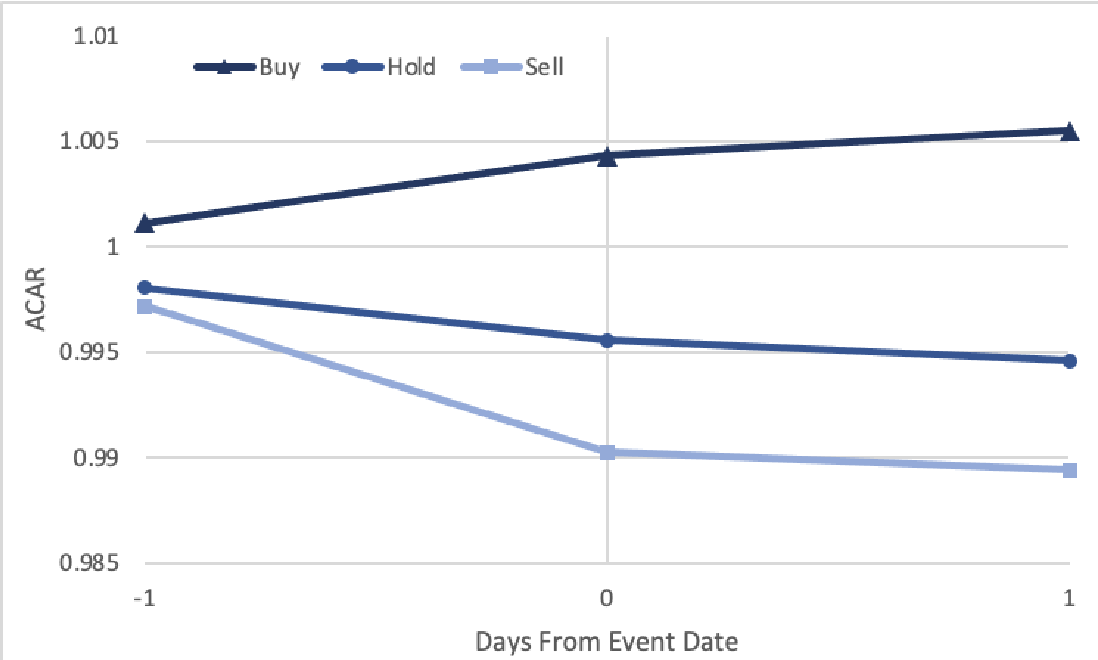

Figure 5.a: Showing the ACAR in the (-1,1) event window for the different recommendations.

In Figure 5.a above, we present the ACAR for the (-1,1) event window. This event window captures the immediate reactions on the day the recommendation is issued, the day after, and the direction of the price on the day before. All ACAR results are computed with a starting value of 1, the day before the event window begins. When buy recommendations move above 1.005 this means the average cumulative abnormal return is above 0.5%.

Figure 5.a shows several interesting traits. Both the hold and sell recommendations are preceded by a negative cumulative abnormal return before the recommendation is issued (-1 day from event date). The opposite can be seen with the buy recommendations, as they on average have a positive cumulative abnormal return before the recommendation is issued. This indicates the direction the stock price is moving before the recommendation is issued. Hold recommendations are associated with negative returns on the stock, causing a drop that mirrors the movement of buy recommendations. Sell recommendations have on average the most drastic effects, leading to ACAR that is the furthest away from the starting value of 1.

5.1.2 Long Event Window

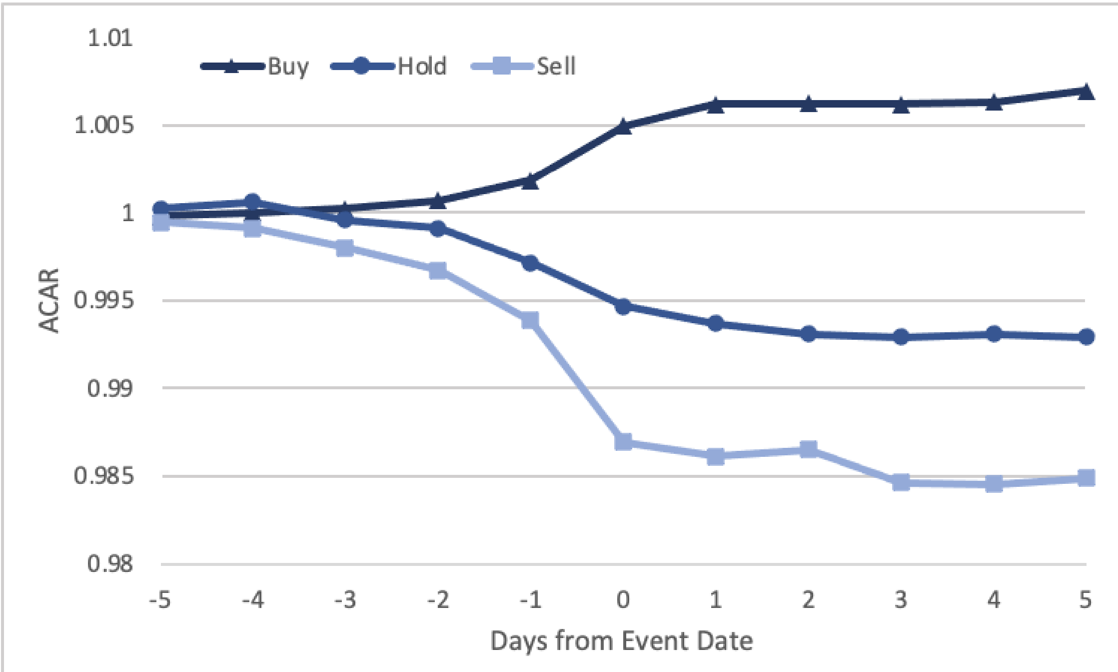

Figure 5.b: Showing the ACAR in the (-5,5) event window for the different recommendations.

In Figure 5.b, we show that buy recommendations yield a positive average cumulative abnormal return (ACAR) of around 0.69% from the (-5,5) event window. A positive average abnormal return on the day the recommendation is issued can be observed, but the ACAR is slightly increasing in the days before this as well. The effect of a sell recommendation is much larger than a buy recommendation with the ACAR moving over -1.5% during the 11-day period.

A comparison of the two event windows shows that much of the changes in ACAR occur during the short event window. For buy recommendations, the ACAR is only 0.15% higher with the extra eight days added. With sell recommendations, the result is -0.45% lower in the long event window. To put it short, the ACAR is, for all recommendations, higher, either positively or negatively, in the long event windows. However, the short three-day event window consists of most of the changes in ACAR that are observed.

	ACAR	Std. Deviation	t-value	p-value	Min	Max	Observations
All recommendations							
[-5,5]	1,000	0,127	-0,090	0,928	-0,325	2,806	27669
[-1,1]	1,000	0,074	2,255**	0,024	-0,098	2,174	27669
Buy recommendations							
[-5,5]	1,007	0,121	5,378***	0,000	-0,064	2,318	15324
[-1,1]	1,005	0,069	9,534***	0,000	0,173	2,100	15324
Hold recommendations							
[-5,5]	0,993	0,126	-1,853*	0,064	-0,325	2,806	8230
[-1,1]	0,995	0,073	-3,594***	0,000	0,151	2,174	8230
Sell recommendations							
[-5,5]	0,985	0,152	-2,820***	0,005	-0,176	2,773	4115
[-1,1]	0,989	0,087	-5,722***	0,000	-0,098	2,005	4115

Table 5.c: Showing statistical values for the ACAR of the different recommendations. Significance levels: * 10%, ** 5%, *** 1%.

Looking at the results from the t-tests in Table 5.c, it is evident that most of the results are statistically significant on one of the significance levels. The only exception is ACAR for all recommendations in the long event window. This means that we have no statistically significant results, to determine the ACAR for a random recommendation, in a (-5,5) event window in this time period. For buy and sell recommendations the results are statistically significant on the 1% level.

5.2 ACAR and Abnormal Volume

In this part, we examine upgrades to buy and downgrades to sell recommendations. We present the ACAR and the abnormal volume for these recommendations, as well as results from the relevant t-tests. Examining upgrades and downgrades separately allows us to exclude the high number of reiterations we have in our dataset.

5.2.1 Upgrades to Buy Recommendations

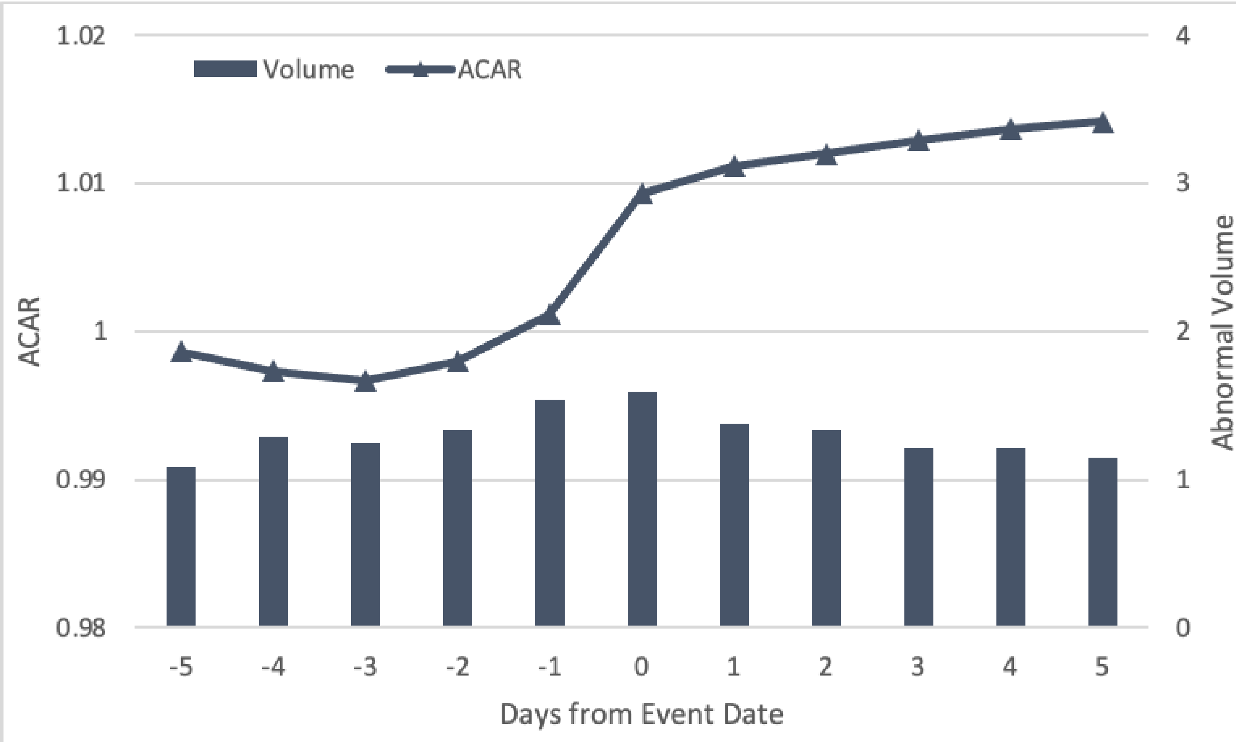

Figure 5.d: Showing ACAR and abnormal volume for upgrades to buy recommendations.

In Figure 5.d we show the ACAR and the abnormal volume when a stock is upgraded to a buy recommendation. This category includes upgrades from sell to buy and hold to buy. We observe that the ACAR is positive when a stock is upgraded to buy and that the volume in the event window is higher than usual.

From Figure 5.d, we can see that during the event window an average upgrade to buy recommendation leads to an increase in a firm's stock price and abnormal return. The ACAR is approximately 1.41% and the largest move in the price appears to occur on the day the recommendation is issued. The recommendation upgrade appears to come at a time when stocks break out of a negative downtrend, as we see that the average cumulative abnormal return is negative in the first three days of the event window. The recommendation change seems to uphold positive momentum in the stocks as it yields positive ACAR in the five days following the recommendation upgrade.

The other observation we make from our data is the increased volume relative to the volume during the estimation window. The volume is above average on all of the event days and is highest on the day the recommendation is issued. On this day, it is approximately 60% higher than average. The second highest volume is usually on the day before the recommendation upgrade. However, the volume is not visibly higher in the days after the recommendation than it is in the days prior.

5.2.2 Downgrades to Sell Recommendations

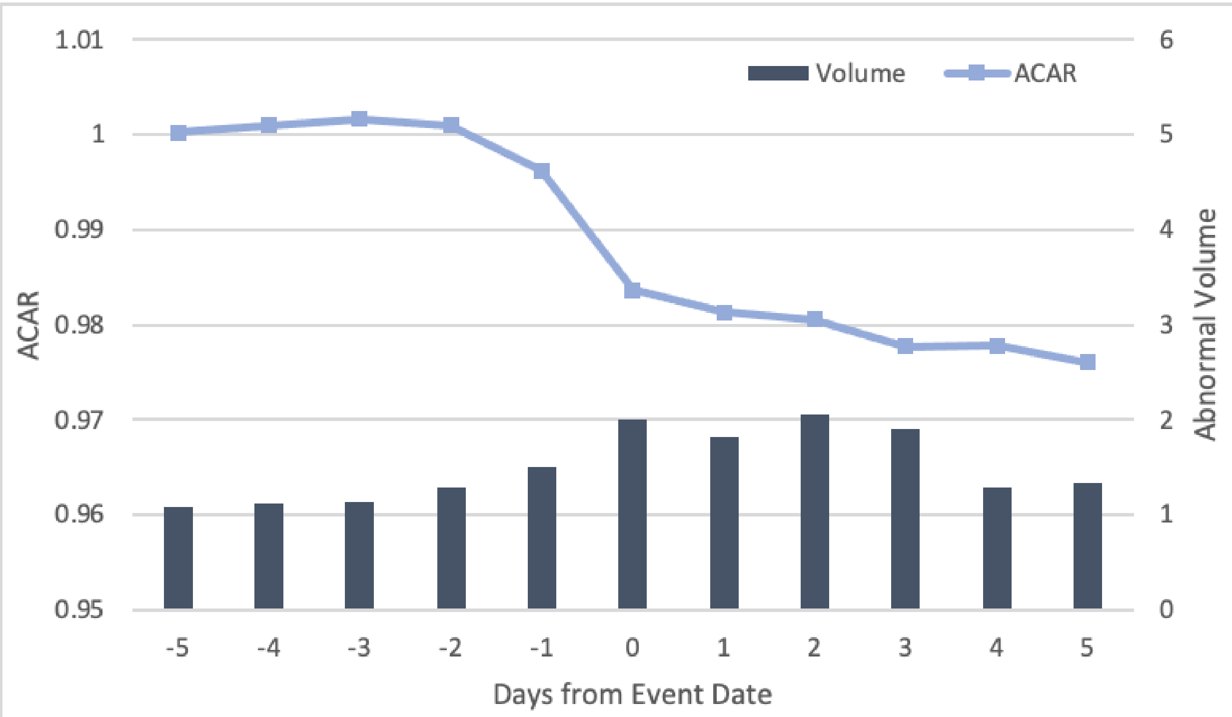

Figure 5.e: Showing ACAR and abnormal volume for downgrades to sell recommendations.

Figure 5.e shows the ACAR and abnormal volume when a stock is downgraded to a sell recommendation. This includes downgrades from buy to sell and hold to sell. We see a definitive fall in ACAR on the day of and after the recommendation is issued. We also see a lasting increase in trading volume.

The ACAR in the event window is approximately -2.4%. This shows that for stocks that are downgraded to sell, there is a visible negative reaction on the ACAR. We also see the increase in volume that occurs on the day of the recommendation and that a high volume is sustained for the next three days. In this period the average volume is around twice as high as in the estimation window and on the highest day, day 2, it is approximately 106% higher. Compared to the upgrades to buy recommendations, downgrades to sell appears to have a much larger impact on the market.

Volume	Avg. event day volume	t-value	Min.	Max.	Observations
All recommendations					
Event day	2 145 015	39,409***	0	246 219 735	27 669
Buy recommendations					
Event day	2 132 859	29,556***	0	246 219 735	15 324
Hold recommendations					
Event day	2 142 523	21,925***	0	152 434 964	8 230
Sell recommendations					
Event day	2 195 268	15,317***	0	173 859 860	4 115
Upgraded to buy					
Event day	2 478 319	11,005***	0	246 219 735	2 457
Downgraded to sell					
Event day	2 579 606	9,014***	0	173 859 860	1 331

Table 5.f: Showing statistical values for event day volume.

Using t-tests, we found that the average event day volume is statistically significant for all the recommendation types listed in the table above with a 99% confidence interval. This shows that the higher volume observed on days that recommendations are issued is not random. We observe that the highest average volume is when stocks receive a downgrade to sell. However, we note that these recommendations also have the smallest number of observations.

Event window	ACAR	Std. Deviation	t-value	p-value	Min	Max	Observations
Upgraded to buy							
[-5,5]	1,016	0,125	4,254***	0,000	0,382	2,232	2 457
[-1,1]	1,015	0,071	9,646***	0,000	0,603	2,100	2 457
Downgraded to sell							
[-5,5]	0,974	0,164	-2,593***	0,010	-0,140	2,773	1 331
[-1,1]	0,979	0,102	-6,491***	0,000	-0,098	2,005	1 331

Table 5.g: Showing statistical values for upgraded to buy and downgraded to sell recommendations.

Performing t-tests on the upgrades to buy and downgrades to sell recommendations yields statistically significant results for both the 11-day and 3-day event windows with a 99% confidence interval. As Table 5.g shows, the effect of a recommendation upgrade to buy and downgrade to sell is slightly larger in the 11-day window in terms of the ACAR. As the longer event window does allow the effect to be observed and cumulate on more days, this is to be expected.

5.3 Comparing with the OSEBX

In this part, a comparison between the ACAR for each year and the annual performance of the OSEBX is presented. Comparing our data to the index allows us to see if the annual performance affects the analyst's ability to yield abnormal returns. Some correlation is to be expected as we study the stocks that are part of the index[12]. We examine both event windows and observe that the results are more varied in the long event window.

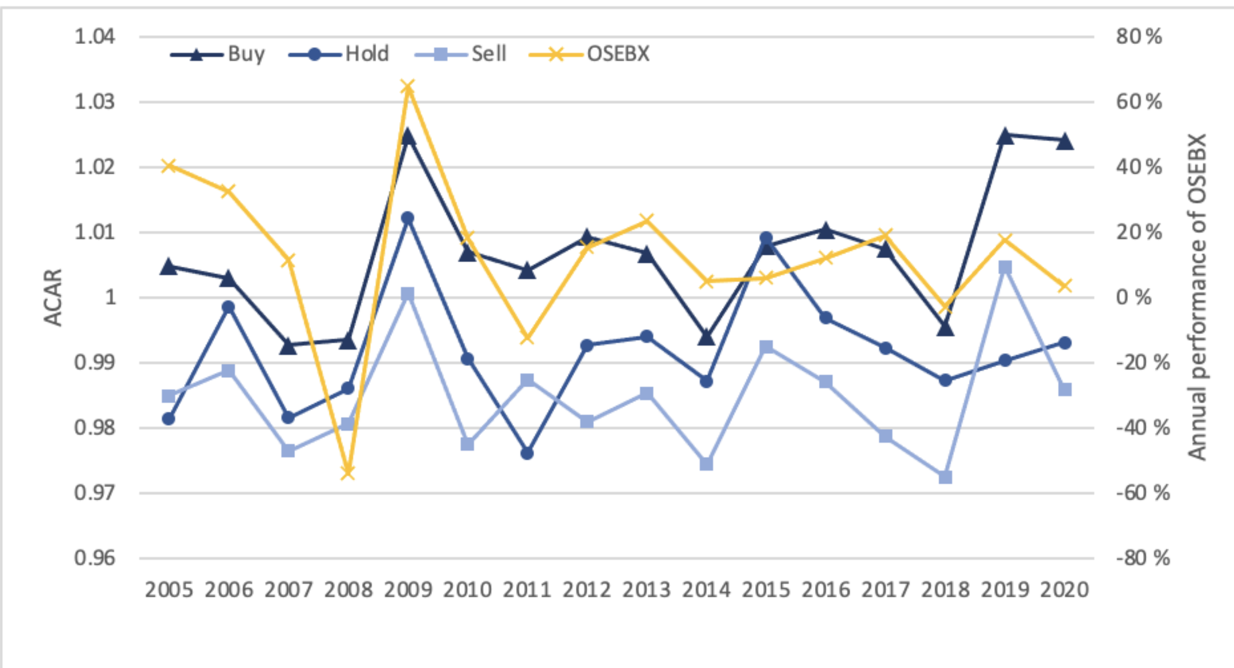

Figure 5.h: (-5,5) Event window ACAR compared to the annual return of OSEBX.

In Figure 5.h, we see that the ACAR for the different recommendations varies greatly from year to year. The buy recommendations always perform better than the sell recommendations. The hold recommendations are a bit more unpredictable, performing better than buy on one occasion and worse than sell on three occasions. Notably, the buy recommendations have had two of their three

[12] The correlation matrix can be found in Appendix 9.1.

best years in 2019 and 2020, despite the OSEBX not performing above average. The third was in 2009 when the index was up over 60%. In these three years ACAR was well above 2% while the fourth best year only has an ACAR of 1%. In four of the years buy recommendations fail to yield a positive ACAR.

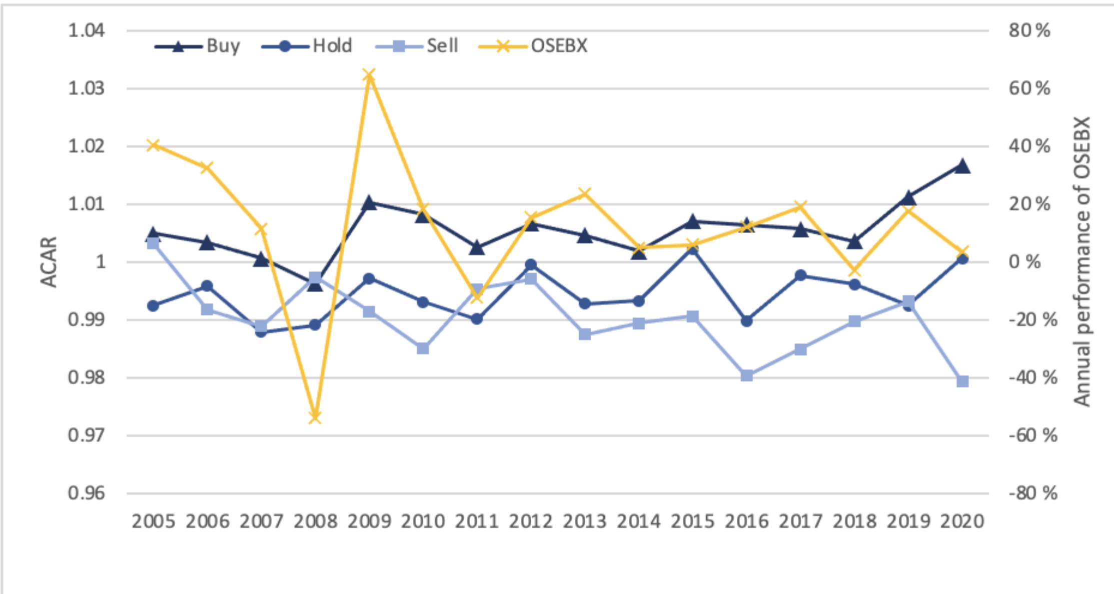

Figure 5.i: (-1,1) Event window ACAR compared to the annual return of OSEBX.

In Figure 5.i, we observe the same trend for the buy recommendations as in Figure 5.h. The ACAR for 2019 and 2020 are the best out of all years, slightly ahead of 2009. Different in this figure, however, is that there is only one year where buy recommendations lead to a negative ACAR. This happened in 2008 where the ACAR was -0.27% and the index was down -54%. Interestingly, the sell recommendations were the top performers this year, though still with a negative ACAR. Sell recommendations yield a negative ACAR in 14 out of 15 years. In the (-1,1) event window, they also have their lowest ACAR in 2020 with a performance of -2.07%. Despite OSEBX having a low annual return in 2020, it was down 31.5% at one point and recorded its highest volatility since 2008.

5.4 Does Size Matter?

In this part, results showing that the ACAR is higher if the recommendation comes from a larger brokerage firm, are presented. Sell recommendations appear to be significantly more influential if they come from one of the top firms and especially *DNB Markets*.

To explore if size mattered, "size" had to be defined. Some alternatives were to look at the number of employees, the number of customers, or even reputation. However, these factors will not be constant throughout the data period. To measure size, we used the number of recommendations issued[13]. We then separated the results from *DNB Markets* and then the next five on the list, to measure their results independently. We measured the immediate reactions from their recommendations, by finding the ACAR in the (-1,1) event window. The results are presented in Table 5.j below.

	Buy (-1,1)	**Sell (-1,1)**
DNB Markets	0.689 %	-2.857 %
Top 5 (excl. DNB)	0.615 %	-1.002 %
The Rest	0.485 %	-0.781 %

Table 5.j: Showing ACAR for the (-1,1) buy and sell event windows. Top 5 are the five largest brokerage firms after *DNB Markets*.

DNB Markets appears to be an influential brokerage firm. It is the brokerage firm that has, by far, issued the most recommendations in the period we are examining. They also appear to be influencing the market more than any of the other firms in the top 5, in terms of stock price movements after recommendations. For sell recommendations there appears to be a greater market movement when the recommendation comes from a large brokerage firm. The ACAR from *DNB Markets´* sell recommendations are 2.8 times higher than the average for the next five firms on the list. For the buy recommendations there is a slightly lower difference, but still favorable results for the top firms. *DNB Markets* have issued 440 sell recommendations, 10.7% of all sell

[13] This list can be found in chapter 3.1.3.

recommendations in our dataset. The second-best performer in the *Top 5* is *SEB Equities*, with 0.657% for buy and -1.865% for sell recommendations. Three of the firms, however, underperform *The Rest* on either buy or sell.

Table 5.k below contains the t-tests conducted on the ACAR, with groupings for the different types of recommendations issued by *DNB Markets*, the next five largest brokers, the remaining brokers and all in total. As the table shows, it is only *DNB Markets* with all their combined recommendations that are not statistically significant at any level. This is likely caused by the combined ACAR of recommendations from *DNB Markets*, as it is very close to the average from the random sample. It is interesting that *DNB Markets* has an ACAR that is the furthest away from the recommendations of other brokers. This is seen amongst the buy, hold, sell, upgraded to buy and downgraded to sell recommendations, and gives further evidence to support the influence *DNB Markets* have through their recommendations. *DNB Markets* is also the only broker where hold recommendations yield an ACAR above 1.

[-1,1]	ACAR	Std. Dev.	t-value	Min.	Max.	Observations
All recommendations						
DNB Markets	0,997	0,087	-0,354	-0,098	1,713	2 786
Top 5 Brokers	1,001	0,071	2,477**	-0,098	1,860	8 494
Remaining Brokers	1,000	0,073	1,952*	0,151	2,174	16 389
All Brokers	1,000	0,074	2,255**	-0,098	2,174	27 669
Buy recommendations						
DNB Markets	1,007	0,077	3,253***	0,173	1,597	1 584
Top 5 Brokers	1,006	0,066	6,384***	0,579	1,781	5 158
Remaining Brokers	1,005	0,070	6,409***	0,429	2,100	8 582
All Brokers	1,005	0,069	9,534***	0,173	2,100	15 324
Hold recommendations						
DNB Markets	1,006	0,085	-2,474**	0,173	1,713	762
Top 5 Brokers	0,995	0,065	-1,699*	0,669	1,521	2 238
Remaining Brokers	0,995	0,074	-2,660***	0,151	2,174	5 230
All Brokers	0,995	0,073	-3,594***	0,151	2,174	8 230
Sell recommendations						
DNB Markets	0,971	0,115	-4,549***	-0,098	1,464	440
Top 5 Brokers	0,990	0,096	-2,999***	-0,098	1,860	1 098
Remaining Brokers	0,992	0,077	-2,931***	0,173	2,005	2 577
All Brokers	0,989	0,087	-5,722***	-0,098	2,005	4 115
Upgraded to Buy						
DNB Markets	1,026	0,070	5,535***	0,807	1,417	312
Top 5 Brokers	1,013	0,069	4,659***	0,730	1,781	1 114
Remaining Brokers	1,011	0,076	5,946***	0,516	2,100	1 902
All Brokers	1,013	0,073	9,134***	0,516	2,100	3 328
Downgraded to Sell						
DNB Markets	0,954	0,134	-4,066***	-0,098	1,172	140
Top 5 Brokers	0,977	0,112	-3,981***	-0,098	1,860	461
Remaining Brokers	0,986	0,085	-4,168***	0,173	2,005	913
All Brokers	0,980	0,100	-6,448***	-0,098	2,005	1 514

Table 5.k: Showing statistical values for the different recommendations in the short event window. Results are presented in categories related to the size of the brokerage firm.

After *DNB Markets*, for all categories in Table 5.k except hold, we see that the *Top 5 Brokers* have a larger influence on the ACAR than the *Remaining Brokers*. As the table shows, they move the ACAR further in each respective direction on buy, sell, upgraded to buy, and downgraded to sell recommendations. The ACAR of the *Top 5 Brokers* hold recommendations are equal to the *Remaining Brokers* ACAR from hold recommendations. In total these results point in the direction of larger brokers having more sway and influence in the market with their recommendations.

5.5 Regression Analysis

Previously in this chapter, we examined the effect a recommendation has on the CAR of a stock. These yielded interesting results regarding the direction and power of stock movements after a recommendation has been issued. Different types of recommendations appear to receive different reactions in the market. In this final part of the analysis, we will perform four regression analyses to examine the effect different independent variables have on the CAR observed in the event window. It will be of interest to see if some variables have a greater effect on some of the recommendation types than others. Therefore, a regression will be run on all the recommendations together, and then on each of the recommendation types, buy, hold, and sell separately.

$$CAR_i = \beta_0 + \beta_1 TP + \beta_2 DM + \beta_3 ER + \beta_4 AL + \beta_5 BE + \beta_6 NO + \beta_7 NR + \beta_8 BU + \beta_9 SE + \beta_{10} FR + \beta_{11} UP + \beta_{12} DW + \beta_{13} DM + \beta_{14} TB + \beta_{15} VM.$$

The dependent variable in the regression will be the cumulative abnormal returns (CAR) estimated from the three-day event window, (-1,1). This event window will have less room for interfering effects from other events than the ones we are examining, namely the issuing of a recommendation. The independent variables are DM, TP, ER, AL, BE, NO, NR, BU, SE, FR, UP, DW, DM, TB and VM. DM is the deviation from the mean target price, showing how far the recommendation target price is from the consensus. TP is the target price of the issued recommendation. ER is the expected return of the stock at the time of the recommendation. AL is the alpha of the stock, and BE its beta at the time of the recommendation. NO is how many recommendations are issued that same day, and NR is how many recommendations are issued on this stock that same day. BU and SE are dummy variables for buy and sell recommendations. FR is a dummy variable for first recommendations, meaning they don't have a previous recommendation from that broker. UP and DW are dummy variables for recommendations that have either been upgraded or downgraded from their previous recommendation level. DM is a dummy variable for recommendations issued by *DNB Markets.* TB is a dummy variable for recommendations issued by the top five brokers that issue the most recommendations after *DNB Markets*. Finally, VM is a variable that contains the volume of the stock on the day of recommendation.

5.6 Regression Results

In this part of the thesis, we will present the results from the regression analysis, and these will be further discussed in chapter 6. Table 5.l is a presentation of the results from the regression analysis. It is divided into four groups, one for the entire dataset with all the recommendations, and then for each of the separate recommendation types[14]. The table contains the coefficients for the different variables with standard errors in parentheses below the coefficients. The coefficients that are significant at a certain level are marked with asterisks, one for when the results are statistically significant at the 10% level, with a p-value smaller than 0.1. Two asterisks when the results are statistically significant at the 5% level, with a p-value smaller than 0.05, and three asterisks when the results are statistically significant at the 1% level, with a p-value smaller than 0.01.

Target price, with the variable TP, have very low coefficients for All recommendation types, and is only slightly significant at the 10%-level for the Sell recommendations. The deviation from the mean variable, VM is statistically significant at the 1%-level for the All category. This variable is measured in percentages away from the mean, which must be considered when viewing the results. Expected return, the variable ER, is statistically significant at the 1%-level for all the recommendation groups, with negative coefficients.

The alpha variable, AL, is significant at the 1%-level for the All and Buy category. Buy has the largest coefficient for the alpha variable, at 2.1063. The beta variable, BE, is only slightly significant at the 10%-level for the Sell category, and is not significant in the other categories. For the variables concerning other recommendations on the same day, NO, the significance results vary. The Hold category yields significant results at the 1%-level for both the NO and NR variable. The All category is slightly significant at the 10%-level for the NO variable, and is significant at the 1%-level for the NR variable. The Sell category also yields significant results at the 1%-level for the NR variable.

[14] The recommendation type categories of the regression analysis are capitalized to allow separation from general referencing to buy, hold and sell recommendations.

Y = CAR [-1,1]	All	Buy	Hold	Sell
Observations:	27699	15324	8230	4115
R-Squared: Adjusted R-Squared:	0,0407 0,0402	0,0266 0,0258	0,0520 0,0505	0,0431 0,0402
Variables:	All	Buy	Hold	Sell
Intercept:	0,9999*** (0,0016)	0,9979*** (0,0018)	0,9990*** (0,0026)	1,0112*** (0,0045)
Target Price: (TP)	-0,0000 (0,0000)	-0,0000 (0,0000)	0,0000 (0,0000)	(-0,0000)* (0,0000)
TP Deviation from mean: (DV)	0,0472*** (0,0022)	0,0478*** (0,0031)	0,0501*** (0,0038)	0,0445*** (0,0059)
Expected Return: (ER)	-3,6093*** (0,2304)	-3,5754*** (0,2945)	-3,9688*** (0,4234)	-3,0136*** (0,6855)
Alpha: (AL)	1,1329*** (0,2815)	2,1063*** (0,3651)	0,0412 (0,5228)	-0,1208 (0,7971)
Beta: (BE)	0,0002 (0,0009)	0,0009 (0,0012)	0,0019 (0,0017)	-0,0048* (0,0026)
Number of Other Recommendations Issued This Day: (NO)	0,0001* (0,0001)	-0,0001 (0,0001)	0,0004*** (0,0001)	0,0003 (0,0002)
Number of Recommendations Issued on This Company This Day: (NR)	-0,0018*** (0,0004)	0,0004 (0,0006)	-0,0049*** (0,0008)	-0,0039*** (0,0013)
Buy: (BU)	0,0005 (0,0011)			
Sell: (SE)	0,0026* (0,0001)			
First Recommendation: (FR)	0,0042** (0,0021)	0,0063*** (0,0024)	0,0030 (0,0045)	-0,0029 (0,0066)
Upgrade: (UP)	0,0123*** (0,0014)	0,0132*** (0,0015)	0,0108*** (0,0027)	
Downgrade: (DW)	-0,0151*** (0,0015)		-0,0136*** (0,0018)	-0,0183*** (0,0029)
DNB Markets: (DM)	-0,0001 (0,0015)	0,0047** (0,0019)	0,0001 (0,0028)	-0,0173*** (0,0045)
Top 5 Brokers: (TB)	0,0025** (0,0010)	0,0028** (0,0012)	0,0029 (0,0019)	0,0004 (0,0032)
Volume: (VM)	0,0000*** (0,0000)	0,0000*** (0,0000)	0,0000*** (0,0000)	0,0000*** (0,0000)
Standard errors are in parentheses.	*p<0,1. **p<0,05. ***p<0,01.			

Table 5.l: Regression analysis results.

The results for the BU and SE variables are barely significant for the SE variable at the 10%-level, while the BU variable is not significant. Upgrades and downgrades are significant at the 1%-level for each of the regressions, with positive signs for the upgrade coefficients and negative signs for the downgrade coefficients. The variable for recommendations issued by *DNB Markets* is significant for Buy and Sell recommendations at the 5% and 1% levels respectively. For the top 5 brokers the results are statistically significant at the 5% level for the All and Buy category. Volume is statistically significant for all the categories at the 1% level, with very low coefficients.

R-squared is in the range of 0.0266 and 0.0520 for the four different regressions. For the Hold category it is the highest, while it is the lowest for the Buy category. As this is a measure of the explanatory power of the regression, it is quite low. The results of the regression analysis will be discussed and elaborated in chapter 6.

6. Discussion

In this chapter, we will discuss the findings from the previous chapter. We have grouped the discussion into relevant subsections, but there will be some cross-referencing and overlapping topic discussions. First, we start by discussing the results related to ACAR and the volume. Then we move on to size, before finishing with a discussion regarding the results of the regression analysis.

6.1 ACAR

We observe that hold and sell recommendations yield a negative ACAR in both event windows, while buy yields a positive ACAR. Buy and hold recommendations are almost mirror opposites in movement, suggesting that investors perceive hold recommendations as the negative counterpart to buy recommendations. Out of all the recommendation types, sell recommendations produce the largest movement in ACAR, away from the starting value of 1. This observation may suggest that sell recommendations are viewed by investors as a more drastic recommendation than other recommendations. However, as there are fewer sell recommendations, it affects the ACAR compared to other recommendations with larger samples.

The results in this thesis show larger movements in ACAR, for all three recommendation types, than Goksøyr and Grønn (2019) did in their thesis. Most notable is the effect of sell recommendations. With it being more than twice as large, it could indicate that the effect of a recommendation is larger for companies with a smaller market cap. This could also be affected by the differences in the number of recommendation changes versus reiterations, presented in chapter 4.6. However, it would be consistent with the findings of Loh and Stulz (2010).

From Table 4.g we see that in total, more recommendations lead to a negative CAR than positive. We find this interesting, as only around half of the buy recommendations lead to a positive CAR, despite being the most numerous recommendation type in the dataset. As we observe significant results for buy recommendations, this could suggest that the recommendations with positive CAR contribute more towards the difference in ACAR than the recommendations with negative CAR does. It is worth noting that approximately 46% of all the recommendations yield CAR in opposite directions of the perceived market reaction to the recommendation. This suggests that the price-moving effect of analyst recommendations can be fickle.

Looking at the yearly comparison between ACAR and OSEBX annual returns in Figure 5.i, there are inconsistent performances for the ACAR. The results in 2020 were rather unique, especially for buy and sell recommendations in the three-day event window. In 2020, buy recommendations had a higher ACAR than any other year in the period, and sell recommendations had the lowest ACAR of the period. 2020 was an interesting year for the stock market, starting with a crash in February from concerns of the growing Covid-19 pandemic, before swiftly rallying in late March. This period saw a sharp increase in retail investors, who might be more reliant on analyst reports. There were approximately 91 thousand new private investors on Oslo Børs in 2020, an increase of over 26% from the year before (Nilsen, 2021). It is not unlikely that new investors with limited knowledge of the market would pay attention to analyst recommendations as a source of information. The increased flow of information, together with online and retail trading being cheaper and more available than before, could be factors that lower the bar of entry for new investors, and increase the number of transactions. Increased volatility from the crash and rally might also be affecting the ACAR observed in 2020.

We can not say for certain that it is the recommendations that are the cause of the ACAR results. We strongly suspect that firm-related news is present around many of our events and thus is a contributing factor in the stock price movements. We reduced our recommendation sample by 20.4% because of recommendations that were issued around earnings releases, and it seems likely that other news is a potential trigger for recommendation changes as well. Be that firm-specific news, sector-specific news, or market news.

6.2 Volume

From our results, we find that volume appears to increase in the days before and after the recommendation. This applies to all recommendations. Only for downgrades to sell, did we find a spike on the event day that indicated the reaction came mostly from the recommendation. For upgrades to buy, the volume appears higher in the days before the recommendation than the days after. However, we see that it peaks on the event day.

As shown in Figure 4.h, our results indicate that buy and hold recommendations on average have a higher abnormal volume the day before, than on the day of the actual recommendation. It is possible that many recommendations are issued the day after important firm news, and that this affects our results. There is also the possibility that there are errors in the dataset regarding the reporting of recommendation issuing to Eikon, as there might be time differences in the recording process that skew the data. We have focused on the removal of earnings reports and have not attempted to identify other firm-specific events. Thus, there could be several explanations for the volume peaking the day before the event. The increased volume observed in the event periods could imply that recommendations are issued in periods with more market activity than usual, and not necessarily that it is the recommendations that drive up the volume.

Womack (1996) conducts research on ACAR and abnormal volume in his paper and our findings are in several ways similar to his. The exception is from the fact that Womack finds much higher abnormal returns than us. The ACAR curve for upgrades to buy recommendations is, despite this, almost identical to the one Womack (1996) presented. The abnormal volume peaks on the event date in both studies. However, in the Norwegian market, the volume on the event day is not as high as it was in the American market. These results indicate that the Norwegian market has, on average, reacted very similarly to how the American market reacted when a stock was upgraded to buy, in the respective time periods.

Comparing downgrades to sell recommendations, the ACAR curve is quite similar and the negative abnormal return is a bit higher in Womack´s (1996) findings. However, the high sustained abnormal volume that follows in the three days after the downgrade, is a unique finding in our study. Womack (1996) finds a lower abnormal volume in two of the three days following the recommendation, compared to the corresponding days prior. Nonetheless, in the Norwegian market, the volume peaks two days after and may indicate that investors are slow to absorb the news. This can be linked to the size of the Norwegian market and the fact that it perhaps is less researched than the American market.

6.3 Size

The results from Table 5.j show that *DNB Markets* outperform the *Top 5 (excl. DNB)*, which again outperformed *The Rest*. We find that size appears to matter for both Buy (-1,1) and Sell (-1,1) recommendations. Compared to Womack (1996), the size of the American brokerage firms and market capitalization of the companies in his study may explain why the ACAR and abnormal volume exceeds the results we find on OSEBX.

The outperformance by the larger brokerage firms in our thesis may depend on other factors than just the number of recommendations. Having the most recommendations would suggest that the ACAR could be closer to the recommendation mean than for brokers with fewer recommendations, not the other way around. For *DNB Markets*, we believe their reputation and number of customers are likely to contribute to the effect their recommendations have on ACAR. They also publish much of their analyses for free, which means the information is public immediately after its release. It is also important to mention that the Norwegian financial media appears to pay great attention to recommendations. This may contribute to making the recommendations of the large brokerage firms more influential, as they are read by a larger audience.

The difference in ACAR between the top firms and the rest is greater for sell than buy recommendations. In general, we have observed that the effect sell recommendations appear to have on the market is larger than the effect from buy recommendations.

6.4 Regression

The four regression analyses conducted in chapter 5 gave some interesting results regarding the effect the different variables have on the recommendation types. Firstly, we find it essential to discuss R-squared. The R-squared values from all four regression analyses were less than 6%, even as low as 2.66% for buy recommendations. These R-squared values are in line with the results from Murg et al. (2016), who studied the effects of stock recommendations in Austria. However, the low R-squared values in our regression analyses suggest that the independent variables do not explain all the variation in CAR during the event window. This is as expected, as we believe that other variables influence the price movements of a stock. Our main interest in the regression analysis is to view the separate effects the variables from the dataset have on the CAR in the event window.

Our results show that the target price, variable TP, is not significant for any of the categories. The explanation could be the target price itself does not matter, it is how far the target price is from the current stock price and analyst consensus. The variable DV, target price deviation from the mean, is statistically significant at the 1% level for all the categories. The results show that the further away from consensus the target price of a recommendation is, it increases the CAR of the stock. With the assumption that the market listens to analysts, this seems plausible, as an analyst promoting a stock as being worth more than what the market perceived from the previous consensus could lead to an increased interest in the stock. If a stock currently is trading at 40 NOK with a mean target price from previous recommendations at 45 NOK, a new buy recommendation with a target price of 70 NOK can lead to increased activity from investors, and thus an increased CAR. This would also coincide with the finding of Loh and Stulz (2010), that deviations from the consensus are linked with higher abnormal returns.

The variable for expected return is statistically significant in all categories, with a negative coefficient sign. A feasible reason for these results may be that the expected return is used in the calculation of the CAR, where a higher expected return yields a lower CAR. This is why the coefficient has a negative sign. The alpha variable refers to the excess return of a stock compared to the index. This variable is significant for the Buy and All categories. As buy recommendations make up more than half of the total dataset, it may be the effect from the Buy category that causes the alpha of the All category to be significant. Buy recommendations, as seen earlier, are most often reiterated, suggesting that they have had a positive track record with excess returns in comparison to the market. The beta variable is only slightly significant for the Sell category at the 10% level. Beta refers to the volatility of the stock compared to the market. For sell recommendations, this would mean that a higher beta might cause the CAR to decrease.

Next, we examine how other recommendations on the same day might affect the CAR movement of the stock. The variable NO, the number of recommendations issued the same day on other stocks, yields some interesting results, despite only the Hold category being significant at the 1% level. The coefficients are negative for the Buy category, and positive for Hold and Sell. A possible explanation for this is that more recommendations on the same day as a buy recommendation dilutes the positive impact of the recommendation in the market, as investor attention could be divided amongst several recommendations. The opposite would then be the case for hold and sell recommendations, that on average seems to lead to negative CAR. The sign is positive for these two categories, and following the reasoning for the Buy category, the negative effect on the CAR of hold and sell recommendations are diluted by other recommendations issued that same day. For the NR variable, the signs are reversed, and three of the categories are significant at the 1% level. Where the NO variable showed possible signs of diluting investor attention, NR amplifies the focus on the stock, measuring the effect of more recommendations on the same stock that day. From our results, the Buy category has a positive coefficient, pointing toward increased CAR when there are more recommendations on the stock that same day. The effect is negative for the Hold and Sell category, with more recommendations causing a decrease in CAR.

The FR variable, covering whether a recommendation is the first recommendation issued by a broker on the company, is statistically significant at the 1% level for the Buy category. The coefficient suggests that there is a positive effect when the initial recommendation is a buy or hold recommendation and a negative effect for sell recommendations. The coefficients are sufficiently smaller than the other two variables also examining the previous recommendation level, namely the UP and DW variables that cover upgraded and downgraded recommendations, respectively. Both variables are significant at the 1% level in each of the categories. Upgraded recommendations are not included in the Sell category, and downgraded recommendations are not included in the Buy category, as that is impossible. The results suggest that there is a positive effect on the CAR of both the Hold and Buy categories from upgrades, and a negative effect on the CAR of the Hold and Sell categories from downgrades. It is of interest to note that the negative coefficient from Sell is larger than the coefficient from Buy. This is consistent with our previous findings in this thesis regarding the negative impact on CAR from sell recommendations being greater than the positive impact from buy recommendations.

Now to the variables regarding the brokers. For the variable DM, recommendations issued by *DNB Markets*, the results are statistically significant at 5% and 1% for the Buy and Sell category, respectively. The coefficients suggest that the market reacts stronger to negative than positive recommendations from *DNB Markets*. For the recommendations issued by the five brokers with the most recommendations after *DNB Markets*, the variable TB is used. The results are significant at the 5% level for the categories All and Buy. In contrast to the DM variable, there appears to be a weak positive CAR effect on the Sell category. This finding is inconsistent with previous results in the thesis, where there appears to be a negative effect when the top five brokers issue sell recommendations. The weak positive CAR effect from the Sell category is however not statistically significant.

Finally, the volume variable VM is statistically significant at the 1% level for all four categories. The coefficients are very small and positive. As the daily traded volume of a stock can be in the millions, it was not unexpected that the coefficients would be small. The results point to a positive effect on the CAR of stock when volume increases.

7. Conclusion

The goal of our thesis has been to explore how the Norwegian market reacts to stock recommendations. Based on former studies, news articles and visible market reactions, the effect of recommendations on the Norwegian market has been unclear. We have aimed to measure the cumulative abnormal return and abnormal volume surrounding stock recommendations on stocks of the OSEBX index, as well as distinguishing traits that may cause a recommendation to have a larger impact.

By applying the event-study methodology from MacKinlay (1997), we find that the average cumulative abnormal return for buy, hold, and sell recommendations are 0.548%, -0.542%, and -1.060%. These are the results from the (-1,1) event window, all being significant on a 1% level, implying that recommendations have some informational value for investors. However, we can not claim causality between recommendations and ACAR. Yet, we believe there is evidence to support correlation.

After reviewing our results, we believe there is a causal effect between *DNB Markets* issuing a sell recommendation, and the stock immediately yielding a negative ACAR. We believe the reaction is enhanced by the press coverage, but not dependent on it. Further on, we do not have any proof that recommendations lead to higher volume. It might as well be that the higher volume originates from other events that lead to the issuing of recommendation changes. However, we believe there is some correlation between increased volume and recommendations.

From the regression we believe that the following variables are correlated with abnormal returns:

- Upgrades (downgrades) are significant and increase (decrease) ACAR;
- Target price deviation from the mean matters for all recommendation types;
- If more negative recommendations (hold or sell) are issued on a company on the same day, the ACAR decreases further;

- If the initial coverage recommendation of an analyst is a buy recommendation, that improves ACAR further than reiterations;
- The market appears to be influenced by buy and sell recommendations from *DNB Markets*, leading to further movements in ACAR than from other brokers;

Based on our findings, we do not believe the Norwegian market has a strong-form market efficiency, and we question if it is even semi-strong. In addition, we are not under the assumption that all recommendations have informational value. This belief is supported by the high number of recommendations yielding a CAR in the opposite direction of the ACAR. However, accompanied with the right traits, we believe recommendations can cause considerable market reactions.

7.1 Weaknesses of the Thesis

The writing and data collection process of a thesis of this scope is filled with decisions where the consequences are only revealed later in the process. Naturally, this means that in hindsight we would reconsider some of those decisions. First, the data collection and sorting process were much longer and time-consuming than expected. Although we knew how to obtain the data, it was challenging to put it in a system that could be used for further analysis. The data collected from the financial software *Refinitiv Eikon* had errors and missing values in it, and a great effort was put into cleaning and filtering the data. There is a high probability that one or more manual errors were committed during this process, which could lead to recommendations being registered at the wrong date. This could also have led to the removal of recommendations meeting the criteria. Using code-based software, such as *Python* or *R* might reduce the risk of committing manual errors. We attempted to learn to code in *R* for this thesis, however, it became clear after some time that it would take more time than we had available. Therefore, we abandoned the idea of coding in *R*.

We decided to filter away recommendations issued in the days surrounding earnings releases. However, there are other company-specific events that could lead to recommendations being issued and increase volume and CAR. Earnings forecasts, management changes, mergers, new contracts, or partnerships are examples of events that could lead to stock price movements or new recommendations. The removal of recommendations issued around such events could lead to a purer measure of the effect recommendations have in terms of CAR and volume.

Ultimately, we must draw attention to the failure to fully comply with the Gauss-Markov assumptions. In part 9.1 in the appendix, we show that the regression contains both heteroskedasticity and autocorrelation. Heteroskedasticity and autocorrelation consistent (HAC) standard errors, could have been applied to neutralize this weakness. The consequence of not doing so is that the R-squared of the regression might show a higher value, than what is correct. The p-values of the regression might show lower values, which means some of the variables we have labeled statistically significant may not be.

7.2 Suggestions for Further Studies

While we are satisfied with the scope and depth we managed for our thesis as a work of one semester, we had to limit ourselves. There were some interesting side topics to our research question that had to be excluded from the thesis. We suggest these topics for further studies, as they could shed light on different aspects regarding stock recommendations. As a result of this, this next section of the chapter will be a short discussion of those topics and suggestions.

We are intrigued to examine whether certain sectors of the stock exchange have a greater response on ACAR from analyst recommendations than others. Another suggestion would be to compare the findings on the Norwegian stock exchange to the stock exchanges in Sweden and Denmark to examine similarities and differences between the countries. By doing so, we can examine if they, similar to the Norwegian market, have large national brokers that influence the market.

A different approach would be to focus more on the brokerage firms and analysts than the actual ACAR. One could examine if brokerage firms influence other brokers with their recommendations, creating common sentiments around the future outlook of the stocks they cover. For instance, how often do brokers issue recommendations that are far away from the mean? It could be very interesting to examine the independence and objectivity of analysts, as well, as there are often business relationships between the company they cover and the brokerage firm that employs them.

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9. Appendix

(-5,5)	*Buy*	*Hold*	*Sell*
OSEBX	0.49619065	0.46956449	0.40006811

(-1,1)	*Buy*	*Hold*	*Sell*
OSEBX	0.4876398	0.28649319	-0.0381096

Appendix 9.1: Correlation matrix between ACAR for recommendations and annual returns of OSEBX. Long event window at the top and short event window at the bottom.

Total Recs	**Brokerage Firm**		
2786	DNB MARKETS	371	Anonymous 11
1975	NORNE SECURITIES AS	290	Anonymous 12
1850	Anonymous 1	270	Anonymous 13
1696	Anonymous 2	248	EXANE BNP PARIBAS
1498	SEB EQUITIES	226	SOCIETE GENERALE
1475	ARCTIC SECURITIES	206	Anonymous 14
1438	Anonymous 3	204	Anonymous 15
1411	PARETO SECURITIES AS	181	NOMURA
1374	Anonymous 4	175	Anonymous 16
1371	FIRST SECURITIES	171	BERENBERG
1085	Anonymous 5	154	Anonymous 17
924	FEARNLEY SECURITIES	152	MACQUARIE RESEARCH
803	SWEDBANK MARKETS	101	CA CHEUVREUX
711	CLARKSONS PLATOU SECURITIES AS (N	89	Anonymous 18
671	Anonymous 6	76	EQUITA SIM
545	Anonymous 7	75	Anonymous 19
524	Anonymous 8	70	ABN AMRO BANK
468	Anonymous 9	67	AGILIS SECURITIES
453	CREDIT SUISSE - EUROPE	61	NATIXIS
443	ALANDSBANKEN	60	Anonymous 20
438	Anonymous 10	58	LEHMAN BROTHERS
404	HSBC		

Appendix 9.2: List of all Brokerage Firms in our dataset, sorted by the total number of recommendations.

Tickers of all the Companies in the Dataset						
ADEV.OL	BON.OL	FASA.OL	KVAER.OL	ODF.OL	SFRET.OL	TRVX.OL
AFGU.OL	BWG.OL	FBUT.OL	KVE.OL	OLT.OL	SIN.OL	TAA.OL
AIK.OL	BWLPG.OL	FIND.OL	LINK.OL	ORK.OL	SME.OL	VEI.OL
AKAS.OL	BWO.OL	FJO.OL	LSG.OL	OTELLO.OL	SNI.OL	VIS.OL
AKER.OL	CATCH.OL	FKRAFT.OL	MAMUT.OL	PAR.OL	SOIF.OL	VIZ.OL
AKERBP.OL	CEQ.OL	FRO.OL	MEDS.OL	PCIB.OL	SOLON.OL	VME.OL
AKES.OL	COPE.OL	FUNCOM.OL	MGNR.OL	PGS.OL	SONG.OL	WALWIL.OL
ALGETA.OL	CRAT.OL	GAMO.OL	MOWI.OL	PHO.OL	SRBANK.OL	WAVE.OL
ALTIN.OL	CRAYON.OL	GJES.OL	MPCC.OL	PLCS.OL	SST.OL	WEIFA.OL
AMEP.OL	CRU.OL	GOGL.OL	MULI.OL	POSF.OL	STB.OL	WWI.OL
ARCZ.OL	DAT.OL	GOL.OL	NEL.OL	PRFD.OL	STP.OL	XXLA.OL
ARRI.OL	DDASA.OL	GRE.OL	NER.OL	PRON.OL	STRONG.OL	YAR.OL
ASC.OL	DNB.OL	GRIA.OL	NEXT.OL	QEC.OL	STXEUR.OL	
ASD.OL	DNO.OL	HEX.OL	NHY.OL	QFR.OL	SUB.OL	
ASETEK.OL	ECHEM.OL	HNA.OL	NKR.OL	RCL.OL	SUBC.OL	
ATEA.OL	EKO.OL	IBAS.OL	NOD.OL	REC.OL	SUO.OL	
ATG.OL	ELK.OL	IDEX.OL	NOFI.OL	RENO.OL	TAT.OL	
AUSS.OL	ELTEK.OL	IMAREX.OL	NORGAN.OL	RIE.OL	TECE.OL	
AVANCE.OL	EMGS.OL	ITER.OL	NORMAN.OL	SALM.OL	TEL.OL	
AWO.OL	ENTRA.OL	JINH.OL	NORN.OL	SASNOK.OL	TGS.OL	
B2H.OL	EQNR.OL	JSHIP.OL	NORR.OL	SATSA.OL	THIN.OL	
BAKKA.OL	EURS.OL	KITR.OL	NPRO.OL	SBSTA.OL	TIETOO.OL	
BDRILL.OL	EVRY.OL	KOA.OL	NRC.OL	SBSTB.OL	TLX.OL	
BEWW.OL	EXPERT.OL	KOG.OL	NSG.OL	SCATC.OL	TOM.OL	
BGBIO.OL	FARA.OL	KOM.OL	OCRA.OL	SDRL.OL	TRIBN.OL	

Appendix 9.3: Tickers of all the companies in the dataset. Listed in alphabetical order.

9.1 Gauss-Markov Assumptions

In our estimation, we use time series regression. The Gauss-Markov assumptions for time series tells us whether the predicted coefficients contain bias and if the estimators are normal. When all assumptions hold, t-statistics can be used for testing the statistical significance of individual explanatory variables, and F-statistics to test for joint significance (Wooldrigde, 2013).

1. **Linearity in parameters**

   Linearity in parameters assumes that the dependent and independent variables follow a linear model. Meaning that an increase in Y is linked to an increase in X, and vice versa. We find linear relationships between our dependent and independent variables.

2. **Non-perfect collinearity**

   “In the sample, none of the independent variables are constant and there are no exact linear relationships among the independent variables” (Wooldrigde, 2013). Independent variables can not be perfectly correlated. We apply the variance inflation factor (VIF) test to examine this. If this test shows values over ten for any of the variables, there is a problem with collinearity. We find that none of the independent variables have a VIF value above three. There is no perfect correlation between the independent variables.

3. **Exogeneity / zero conditional mean**

   “For each t, the expected value of the error u_t, given the explanatory variables for all time periods, is zero” (Wooldrigde, 2013). Failure to meet this assumption, means probably over- or underestimating the coefficients. To check this, we use the Durbin Watson test, which is actually for autocorrelation. For stock prices, this test tells us if the return on one day is correlated with the return on the previous day. This test on its own is not a guarantee for having exogenous explanatory variables. The Durbin Watson test fails to eliminate the possibility of autocorrelation. However, this does not mean the data fails to meet this assumption. We are unable to conclude whether the data fulfills this assumption but assume it does.

4. Homoscedasticity

Conditional on X, the variance of $u_t$is the same for all t:

$$Var(u_t|X) = Var(u_t) = \sigma^2, t = 1,2....n .$$

This means that the error term, u_t, and the variable, X, must be independent and that the variance of $u_t$is constant over time. When this assumption does not hold, we say that the errors are heteroskedastic. The Breusch-Pagan test, and the Whites test, are both tests for heteroskedasticity. They follow the same null hypothesis which is that the data is homoscedastic. The Breusch-Pagan test explores if the errors are a linear function of one or more independent variables in the model, where the squared residuals are used as estimates on the variance of the errors. If there is no correlation between the squared residuals and the model, we have homoskedasticity (Breusch & Pagan, 1979).

Whites test follows the same method as Breusch-Pagan. However, it includes more squared predicted values which lead to more combinations in the regression and more test estimates than Breusch-Pagan. One advantage of Whites test is that it makes few assumptions about the form of heteroskedasticity it looks for.

From the Breusch-Pagan test, we find that our error terms are heteroskedastic. This means that our error terms are incorrectly specified. By applying the Whites test as well, this is confirmed. The variance of the stock prices has not been constant in the time period we study. Heteroskedasticity can lead to p-values that are smaller than they should be.

5. **No serial correlation**

Conditional on X, the errors in two different time periods are uncorrelated. For simplicity we can ignore the conditioning on X and write the assumption in the following way:

$$Corr(u_t, u_s) = 0 \text{ , } for\ all\ t \neq s.$$

To check for autocorrelation, we use the Durbin Watson test. We get a test result of 0.263 for the regression model, which indicates we have positive autocorrelation. Positive autocorrelation is common in time series data. However, this means that the R-squared might show a higher value than it should.

6. **Normality**

The errors u_t are independent of X and are independently and identically distributed as normal (Wooldrigde, 2013). From Brown and Warner (1985) we know that the distribution of abnormal returns for stocks is fat-tailed relative to a normal distribution. However, as the sample of abnormal returns increases, and the number of stocks increase the distribution will converge towards normality. The issue is how large the sample must be to be normally distributed. Using the Shapiro-Wilks test, we find that our data is almost perfectly normally distributed.