Norwegian School of Economics
Bergen, Fall 2021

The Impact of Sell-Side Research in the Norwegian Stock Market

An Empirical Investigation of the Relationship Between Sell-Side Reports, Stock Returns and Trading Volume on Oslo Stock Exchange

Jesper Rugland and Jarle Volden

Supervisor: Roberto Ricco'

Master thesis in Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

This thesis was written as a part of the Master of Science in Economics and Business Administration at NHH. Please note that neither the institution nor the examiners are responsible − through the approval of this thesis − for the theories and methods used, or results and conclusions drawn in this work.

Preface

The completion of this thesis is an important milestone in our academic journeys, and it marks the imminent completion of our Master of Science degrees in Financial Economics at the Norwegian School of Economics. We wish to express our sincerest gratitude to our supervisor, Roberto Ricco', who has provided us with valuable insight and support along the way. We also wish to thank the Norwegian School of Economics for access to relevant databases and literature.

Norwegian School of Economics

Bergen, December 20th, 2021

Jesper Rugland

Jarle Volden

Abstract

This paper examines the impact of sell-side research on stocks listed on the Oslo Stock Exchange by identifying the incremental changes to the stock returns and the trading volume for the OBX Index constituents, using a sample of 477 manually collected sell-side reports issued between 2016 and 2020. In line with prevalent academic research on identifying incremental changes to stock returns and trading volume, this paper employs the event study framework to identify said changes on an individual and aggregate basis for various report characteristics, the OBX Index and index constituents on the day of report issuance.

The empirical evidence suggests that sell-side reports generate abnormal trading volume on the day of report issuance. There is also evidence to support abnormal trading volume on the day prior and the first few days following report issuance. Furthermore, reports accompanied by upgraded recommendations have the most significant impact on trading volume, but the evidence also suggests that reiterations and downwards revisions generate abnormal trading volume. In contrast, this study finds no evidence to support that sell-side reports generate abnormal returns for the OBX Index constituents collectively on the day of issuance. However, reports where a recommendation is revised upwards or downwards generate abnormal returns.

This paper finds heightened interest in the researched securities on the day of report issuance, using trading volume to measure investor recognition. The heightened interest in the security in question does not translate to a decisive impact on returns on issuance, but the evidence suggests that there is a significant abnormal return on the first day following issuance. The findings are economically important in the sense that they complement the notion that analysts play a vital role in increasing investor recognition for covered companies (Merton, 1987) while compensated for doing so (Groysberg et al., 2011), and support that this notion holds for the Norwegian stock market as well.

Contents

1. Introduction

In this paper, we investigate the relationship between sell-side reports, stock returns and trading volume in the Norwegian stock market, based on the OBX Index constituents[1] as of June 30th, 2021 (Euronext, 2021). The OBX Index is an index that features the 25 most liquid stocks on the Oslo Stock Exchange and is revised semi-annually. The basis for investigating such relationships is to identify whether analysts provide value-add to their employer and investors.

Securities research is a discipline within the financial services industry, primarily divided into *equity*- and *credit research*[2]. Equity research analysts cover commonly traded stocks, whereas credit research analysts cover fixed income securities. Securities research can be classified as either sell-side or buy-side research. The focus throughout this paper will be on sell-side research.

Sell-side equity research analysts[3] work on the sell-side of the capital markets, and they are predominantly employed by investment banks and other advisory firms mandated by companies to aid in capital markets transactions or to provide other types of advisory services for a client. Although a sell-side analyst's role is composed mainly of analysing companies and issuing reports, there are some differences in the analyst's role depending on whether it is a primary market transaction or if the securities are trading in the secondary market.

Sell-side equity research analysts are often conferred on transactions that the advisor assists during a primary market transaction. However, they are separated from the firm's investment banking division to provide non-classified information to the investors. When this is the case, the equity research analyst will be given a detailed run-through by the investment banking team and the issuing agent to be as informed as possible and convey meaningful information to investors where applicable. However, equity research analysts are more frequently observed and encountered in the secondary market. Analysts will typically cover a range of companies within a specific industry that they analyse. An analyst will start coverage of a new firm by issuing an Initiation of Coverage (IoC) report, proceeded by updates/revisions to this report when the company releases interim and annual statements and various events of importance

[1] OBX constituents referred to as "sample companies" throughout the paper.
[2] Credit research can also be referred to as Fixed Income research.
[3] Sell-side equity research analysts are referred to as "analyst", "sell-side analyst" and "equity research analyst" throughout this paper.

(firm-specific news). In most cases, these reports include an earnings estimate, a valuation range, a target price, and a purchase recommendation[4] for the company.

Although reports issued by analysts may merely be conceived, by some, as guidance for investors, academic papers show that analysts play an essential role for the companies they cover in the capital markets. Merton (1987) argues that equity research analysts can contribute to lowering a company's cost of capital, which leads to a higher stock price, by increasing the overall recognition of the company among investors. Merton builds on the assumption that there is an equilibrium in the market, where low-demand stocks trade at a lower price due to investors holding stocks they are familiar with. Analysts play an essential role in promoting companies to investors, and according to Merton, they actively contribute to increasing the firm value for the companies they cover. Numerous academic studies find the same negative relationship between investor recognition and cost of capital, for instance, Richardson et al. (2012) and Huang & Wei (2012).

Groysberg et al. (2011) found, by analysing proprietary compensation data provided by a leading U.S. investment bank and research reports between 1988 and 2005, that analysts' compensation is closely tied to their ability to sell securities on behalf of their bank's sales force (brokers) and investment banking business. However, other factors influence their compensation, such as ratings based on their accuracy.

To investigate whether there is any value-add from sell-side reports concerning the OBX Index constituents, we examine whether these reports have any material impact on the sample companies in terms of stock returns and trading volume. In this study, we have deemed trading volume the primary determinant of investor recognition, whereas returns are the primary determinant of value-add to investors. We make an essential assumption that the same relationship between compensation and analysts' ability to sell securities, as presented by Groysberg et al. (2011), and the cost of capital contribution found by Merton (1987) holds for analysts operating in the Norwegian market. The rationale for this thinking is that increased trading volume leads to higher compensation for the analyst, and it implies a heightened investor interest in the stock, whereas returns display the value-add for investors if the investor follows the analyst recommendations.

[4] Common recommendations are "buy", "hold" and "sell", but can also include other variants and additional recommendations such as "strong buy" and "strong sell".

Based on our observations, we believe that investors operating in the Norwegian stock market are more likely to read or observe analyst recommendations either through their broker or through the Norwegian financial press than those who are not. As such, we find that the Oslo Stock Exchange and the recommendations of select analysts covering the OBX Index constituents to be a valid starting point for exploring such relationships.

2. Theoretical framework

This chapter presents various literature and concepts that we believe provide an important backdrop for this study. Firstly, we introduce the Efficient Market Hypothesis in Section 2.1, followed by early criticism of efficient markets theories in Section 2.2. Lastly, in Section 2.3, we present the Adaptive Market Hypothesis, an alternative theory to the Efficient Market Hypothesis.

2.1 Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) is a well-established and controversial concept in financial theory. The EMH as we know it today has developed over the years with known references to efficient markets dating back to 1889 in a book titled *The Stock Markets of London, Paris and New York* by George Gibson (Gibson, 1889). Although there have been many contributions to the research on market efficiency, Eugene Fama is arguably one of the most notable academicians concerning market efficiency and in the field of economics, having received the Nobel Prize in 2013 for his works. In one of his most well-known works, *Efficient Capital Markets: A Review of Theory and Empirical Work*, Fama (1970) argues that a market is efficient if the price fully reflects all available information.

According to Fama (1970), there are three forms of efficient markets; weak, semi-strong and strong[5]. In the *weak form*, the current price reflects all historical prices. In the *semi-strong form*, prices adjust to publicly known information such as stock splits and earnings. All public and private information (insider information) are reflected in stock prices in the *strong form*. The *weak form* excludes investors using technical frameworks from achieving risk-adjusted excess returns. The *semi-strong form* of market efficiency excludes investors from achieving risk-adjusted excess returns with technical and fundamental frameworks, meaning that the only way to achieve such returns is to act on insider information (i.e. non-public information). The *strong form* of market efficiency makes it impossible to achieve risk-adjusted excess returns as past prices, public information and insider information is fully reflected in the stock price.

[5] The distinction between weak and strong forms were first suggested by Harry Roberts in 1967 before it was published by Eugene Fama in 1970 (Sewell, 2012).

Although there is academic support for the EMH, some literature argues that it is difficult for the EMH to hold. For markets to be fully efficient and to reflect all available information, it needs to know how to fully reflect this information, which is dependent on investors' risk preferences. As such, a test of the EMH needs to capture investor preferences, and the EMH on a stand-alone basis is said not to be fully supported empirically (Sewell, 2012). The lack of complete empirical support leads us to the *joint hypothesis problem,* which states that measuring market efficiency is complicated and is dependent on asset pricing models to compare expected returns to actual returns (Fama, 1970). Using asset pricing models may lead to abnormal returns, implying that the market is inefficient, the asset pricing model is inaccurate or both. Therefore, the existence of the *joint hypothesis problem* results in the inability to reject the EMH (Campbell et al., 1997). Grossman and Stiglitz (1980) argue that information cannot be fully reflected in the prices because the information is costly. If the markets were fully efficient and reflected all available information, there would be no incentive to search for additional information; hence they conclude that an informationally efficient market cannot exist.

2.2 Early criticism of efficient markets theories

Robert J. Shiller was one of the early critics of the 1970's efficient markets theories. In 2003, Shiller published an article named *From Efficient Markets Theory to Behavioral Finance,* in which he argues that the efficient markets theory is something of the past and had its peak during the 1970s as it aligned with theoretical trends at the time.

Shiller (2003) points to research done during the 1980s, which was an important decade regarding research on the consistency of the efficient markets model. From this research, he questions the excess volatility in studied stocks and whether the efficient markets model can explain this[6]. He notes that although these deviations are minor deviations from the fundamental value predicted by the efficient markets model, unexplained deviations would question the underlying basics of the efficient markets model. Given the efficient markets model equation, any sudden movements in a stock's price should come from new public information. By discounting the dividends paid by Standard & Poor's Composite Stock Price

[6] Efficient markets model equals to the price of a share at time t, denoted P_t, where P_t equals the present value of all subsequent dividends to that share. The present value of these dividend payments are unknown, and have to be forecasted based on all available information (Shiller, 2003).

Index constituents from 1871 to 2002 using the geometric average of real returns for the same index as the discount rate, Shiller (1981) found the present value of dividends to be visualised as a continuous upwards sloping line, whereas the index itself fluctuated. Shiller argues that the difference between the trend line for the present value of dividends and the index shows excess volatility in the aggregate stock market and that no form of the EMH can explain the volatility in the stock market by looking at discounted values of future earnings. It is also unlikely that anyone can adjust the discount rates convincingly to fit the index's price. Should the discount rate be adjusted, it needs to be argued that investors thoroughly understand the events that lead to changes in the future discount rate. Shiller acknowledges the existence of noise in the markets but finds it unlikely for the efficient market hypothesis to hold, given the volatility in the aggregate market.

During the 1990s, academic research saw a sharp development in behavioural finance with less focus on time-series studies on observed prices and earnings. Shiller (2003) highlights two different examples, feedback models and obstacles to smart money.

Feedback models (or price-to-price feedback theory) are, according to Shiller (2003), one of the oldest financial theories. Feedback models are based on word-of-mouth and public attention, for instance, heightened enthusiasm when stock prices go up. Attention is drawn to what Shiller refers to as *new era* or *popular* theories that support further increased demand and price movements to justify the price movements. Should this feedback continue uninterrupted, a bubble can occur where high expectations support high prices. This bubble can burst without any new information that is related to fundamentals. Similarly, feedback models can drive the price downwards until they reach an unsustainable low level and exhibit the same characteristics as the previous example. Albeit they play a small role in daily stock price movements, Shiller argues that feedback models can cause complicated dynamics and explain some of the inherent noise in the stock market. To support this, Shiller refers to evidence from natural and lab experiments, emphasising natural experiments that occur in real-time with real money, such as Ponzi schemes.

Whereas feedback traders base their actions on other people's beliefs, *smart money* traders conduct opposite trades. Shiller (2003) argues that a flaw in the efficient market theory is the bundling of all investors and assuming that they are all rational optimisers and finds it unlikely that all investors can solve complex optimisation models. For the theory to be valid, there would have to be *smart money* that can offset the actions of a larger group of investors for the markets to be efficient. However, the financial theory does not assert that smart money fully offsets normal investor behaviour. A theoretical model that includes both smart money and feedback traders finds that smart money tends to amplify feedback traders' effect rather than offset them by buying stock ahead of feedback traders in anticipation of price rallies (de Long et al., 1990). A similar model found that rational utility-maximising smart money investors never fully offset the decisions made by feedback investors as they do not wish to take on the additional risk that might arise from doing so (de Long et al., 1990). Another flaw in the efficient market theories is restrictions on short selling. Should the stock be overpriced, smart money would short the stock. However, in some cases, there are not enough available shares to short, rendering smart money investors unable to fully offset the actions of feedback investors (Miller, 1977). Thus certain stocks can be overpriced.

Conclusively, Shiller (2003) states that efficient markets theory has its place in describing an ideal world and that they cannot be mistaken for depictions of the actual world. The intersection between financial theory and social sciences is vital in deepening the knowledge of financial markets and is essential for researchers to better their models.

2.3 Adaptive Market Hypothesis

This scrutiny of the EMH inspired the development of a separate efficiency theory, the *Adaptive Market Hypothesis* (AMH). Anchored in principles of evolution, Andrew Lo (2004) proposed that the lion’s share of the behavioural inconsistencies in finance are consistent with evolution and how humans learn to adapt to changing environments. Central to the AMH is the idea that people make mistakes, learn from them, and base their future behaviour on past experiences. In his 2004 paper, Lo underlines that people are generally rational but often react irrationally to heightened market volatility periods, which gives rise to profit-making opportunities. He argues that counterexamples of economic rationality, such as overreaction, overconfidence, loss aversion, and other behavioural biases, are consistent with an evolutionary model in which individuals (buy-side agents) adapt to a changing environment (the market) via minimum effort heuristics. As he points out, this is essentially an extension of Herbert Simon’s (1956) concept of *satisficing*[7]. Thus, according to Lo, the efficiency of the

[7] A word coined by Simon, made up of satisfy and sufficient. As the portmanteau suggests, it is used to describe the behaviour decisionmakers exhibits when faced with an optimisation problem which has no clear optimal solution.

market is ultimately reliant on the Darwinian determinants (adaptation, competition and natural selection[8]) of financial interactions.

The principles of the AMH have several practical implications in finance. Firstly, because of the changing stock market environment and the nature and composition of its participants, the risk premium required will vary over time. To paint a picture of the effect market environments can have, consider the influx of new retail investors stock markets after the Covid-19 crash of 2020. Imagine an investor entering the market for the first time in his career on March 20th, 2020. Since then, the S&P500 has seen an unprecedented bull run, gaining approximately 90% the following 18 months. This investor has never experienced an actual bear market, which will likely shape his risk preference. Conversely, an investor who thought it wise to leverage up and buy a house based on the axiom of ever-increasing house prices, only to witness the collapse of Lehman Brothers and the burst of the sub-prime mortgage bubble of 2007-2008 a couple of months later, will have different expectations and aggregate risk preference. Lo (2004) postulates that humans learn through trial and error and apply this to investment strategies. The bearing implication is that profitable strategies will persist, while unsuccessful ones will cease to exist.

Secondly, under the AMH, consistent with the findings of Grossman and Stiglitz (1980), arbitrage opportunities can and *should* exist from time to time in the market. The process of finding and digesting information is both time-consuming and costly. If no such profit-making opportunity exists in a market, it would likewise remain no incentive for its participants to gather information, ultimately rendering financial markets illiquid, inefficient, and undesirable. The fact that they are not should imply that arbitrage opportunities do exist and, regardless of how quickly they disappear, will continue to reappear as market participants shift their focus based on trends, bubbles and crashes.

Despite the AMH's concrete implications for portfolio management, academics have criticised it for its lack of mathematical evidence due to its qualitative nature.

[8] Natural selection process of market participants assumes that profit-making strategies (skilled investors) will survive, while loss-making strategies (sub-par investors) will go extinct.

3. Literature review

Whereas the previous chapter sheds light on one of the most frequently encountered and controversial concepts in academic, financial theory, namely market efficiency, this chapter covers various literature more directly relevant to our study. Section 3.1 presents some of the pre-existing literature on the impact of sell-side research on stock returns and trading volume. Section 3.2 presents literature on the impact of firm-specific news releases. Section 3.3 concludes this chapter by explaining how our paper differs from previous literature and its contributions.

3.1 The impact of sell-side equity research reports

3.1.1 Impact on stock returns

Abnormal returns refer to extraordinarily gains or losses of a given asset over a given time interval, constituted by a deviation from the expected return attributed by an asset pricing model over the same period. For this thesis, we use abnormal returns to determine the risk-adjusted performance of the analysed stocks in the sample. Several pre-existing academic works study the impact of sell-side analyst reports on stock returns, and in this section, we review various literature that examines such relationships in different stock markets.

The mounting scrutiny on the role of sell-side analysts as investment advisors in the latter part of the 20^{th} century has prompted numerous studies on their actual contribution to market efficiency and abnormal return patterns (e.g., Jung, Sun & Yang, 2012; Souček & Wasserek, 2014; Li & You, 2015; Sun et al., 2017). The scrutiny is not unwarranted, however. Most analyst recommendations tend towards being positively biased, meaning that they rarely issue sell or strong sell recommendations (Jegadeesh & Kim, 2006). Jegadeesh et al. (2004) report that the latter only makes up approximately five percent of issued recommendations and that the average analyst recommendation between 1985 and 1999 constitutes a buy. The findings of Jegadeesh et al. (2004) may well be consistent with what Lin & McNichols (1998) and Michaely & Womack (1999) alluded to – analysts employed by lead underwriters for new equity issuances issue more favourable recommendations for the underwritten stock than what other analysts who also follow the stock does. Despite this inherent bias, evidence from the literature suggests that analyst recommendations add value to investors (e.g., Stickel, 1995; Barber et al., 2001; Green, 2006).

How much value can analysts' recommendations potentially add, and what does this imply for the efficiency of the market? If markets were perfectly efficient, the analyst's role of guiding investors would imaginably be obsolete as market prices already would reflect all available information. To this conundrum, Jegadeesh & Kim (2006) proposes that analysts can add value because of a skillset that allows them to collect and analyse value-relevant information more efficiently than other market participants. By examining the impact of 191,174 analyst recommendations across the G7[9] main stock markets between November 1993 and July 2002 using the event study framework, they find that stock prices react significantly to revisions on the day of recommendation and the following day in all countries except for Italy. Moreover, an upward (downward) drift is observed two to six months after an upgrade (downgrade). The authors then compare recommendations of ADRs[10] followed by both US analysts and non-US analysts. The recommendations of US-based analysts seem to provide more value than non-US-based analyst recommendations. As the US market is the largest in terms of capital and number of participants, it should, too, according to theory, be the most likely to operate efficiently. Jegadeesh & Kim's findings should thus indicate that rather than the US markets being less informationally efficient than other markets, the US analysts are more skilled at identifying undervalued stocks and provide superior value to investors, as evidenced by increased trading volumes, stock price movements, and recognition of the stocks analysed. Overall, analysts in the remaining G7 countries provide only restricted value through recommendations, suggesting that these markets are fairly efficient and that uncovering significant mispricing is unusual.

A study by Sun et al. (2017) examined the relationship between Brazilian Ibovespa Index constituents, 63 stocks[11], and sell-side recommendations collected from the I/B/E/S database for 2014. The study divided recommendations into categories on a scale from 1 to 5, where 1 is a strong purchase recommendation, and 5 is a strong sell recommendation. Sun et al. found that recommendations of level 1 (strong purchase) provided an abnormal return of 0.51% on the day of recommendation with statistical significance at the 5% level. Level 2 recommendations (purchase) provided a positive (cumulative) abnormal return for the day of recommendation (0.45%), three days- and one week (0.55% and 0.52%, respectively) following the recommendation. Recommendations of level 3 (hold) provided negative

[9] Includes the US, Britain, Canada, France, Germany, Italy and Japan.
[10] American Depository Receipt: a certificate issued by a US bank representing a specified number of shares of a foreign company's stock. The certificate trades on a US stock exchange like any domestic share would.
[11] Bovespa Index constituents as of 2014.

(cumulative) abnormal return with statistically significance at the 5% level for the day of recommendation (-0.3%), one month- and three months following the recommendation (-1.48% and -3.59%, respectively). As for recommendations of level 4 (sell), they found statistical significance for the day of the recommendation (-0.99%), one week (-1.47%), two weeks (-1.59%), one month (-1.99%) and three months (-3.02%) following the recommendation. Lastly, they found negative (cumulative) abnormal returns for recommendations of level 5 for all periods, except the three-day window. The cumulative abnormal returns were -0.27% for the day of recommendation, -0.44% for one week, -0.86% for two weeks, -0.38% for one month and -9.29% for three months following the recommendation.

Another study by Su et al. (2018) examines the impact of sell-side analyses on firms listed on the Main Market of London Stock Exchange (LSE) and on the Alternative Investment Market (AIM) between January 1995 and June 2013 using a total of 70,220 sell-side analyst recommendations. Whereas many previous studies on the topic use the event study framework, the study by Su et al. investigates different self-composed portfolios based on the recommendation type and the value they add to the investors. Su et al. constructed an upgrade and a downgrade portfolio, where the upgrade portfolio includes recommendations that have been revised to strong buy or buy, previously being hold, sell or strong sell. Likewise, the downgrade portfolio includes recommendations that have been revised to strong sell or sell, previously being hold, buy or strong buy. The portfolios were updated daily, with revised analyses (stocks) entering the respective portfolio before the next trading day. The portfolios were evaluated on a one-year rolling basis, using the intercepts from both single- and multifactor models. Su et al. found that the upward revisions portfolio generated no statistically significant abnormal returns and concluded that they are of no value to investors. The downward revision portfolio generated statistically significant abnormal gross returns at the 5% level. This abnormal gross return ranges from -3.5 bps to -6.4 bps from April 2001 to January 2003. Between March 2009 and June 2010, this range is -3.45 bps to -8.59 bps. However, this portfolio did not generate any significant abnormal returns net of transaction costs.

A thesis by former NHH students, Goksøyr & Grønn (2019), investigates the impact of sell-side reports on the 25 stocks that constituted the OBX Index as of the beginning of 2019, using reports from 21 different sell-side research providers downloaded from Bloomberg for the period between the beginning of 2007 and the end of 2018. Using the event study methodology, Goksøyr & Grønn found the sell-side reports to generate a significant cumulative average abnormal return of 0.362%, -0.184% and -0.485% for buy-, hold- and sell recommendations respectively with an event-window of t-1 to t+1. Furthermore, they found that the market reaction to the sample recommendations is slight and that the analyst recommendations constitutes a small part of the investor's information base, yet increasingly valuable when shifting consensus.

3.1.2 Impact on trading volume

Jegadeesh & Kim (2006) explore, among previously mentioned points, the effect analyst recommendations have on trading volume in G7 countries. Using a measure of standardised trading volume to examine the pattern of trading volume around a specified event (recommendation) date, they uncover that the standardised volume is significantly different from 1 on days -1, 0 and 1 in all countries except Italy. US stocks experience the largest boost in trading volume, consistent with their theory of US analysts adding the most value. Trading volume reverts to normal within three days of the recommendation revision for all countries other than the US and Japan. The two countries' abnormal trading volumes do not subside until day 7 (8) and day 5 (3) for upgrades (downgrades), respectively. Thus, they conclude that analyst recommendations provide the most value for investors in terms of trading volume in the US and Japan, and investors with ties to these countries trade more active there than in other countries.

Panchenko (2007) examines the impact of approximately 2,000 sell-side recommendation updates on the stock performance of 36 large-cap US stocks from June 1997 to May 2003. Panchenko aims to research further the idea of trading volume as a proxy for the speed of informational flow in capital markets, introduced by Peter Clark (1973). If this is indeed true, analyst recommendations should generate increased trading volumes if they provide the market with new information. Empirically, Panchenko shows, through the event study methodology, that abnormal trading volume clustered around some period before and after the report issuance date, suggesting that Clark's idea is correct. However, a conclusion on this can not be reached as the article fails to provide a tool for measuring "new information". He also analyses volume in the context of something he calls analyst *war* and *peace* periods, where heterogenous recommendations issued by brokerages characterise the former and the latter by the opposite. Not surprisingly, with conflicting recommendations, the war periods generate higher volumes and volatility than the peace periods. The interesting point is that volatility and volumes are twice as high during *war* periods than during periods of concurring recommendations. The behaviour of average abnormal volume is almost identical to the behaviour of average abnormal volatility – which supports the claim that volume can be a good predictor for volatility. Finally, as recommendation updates seem to increase trading volume, they increase the liquidity of the stock in question and overall market liquidity.

3.2 Impact of firm-specific news

In a paper titled *Are Economically Significant Stock Returns and Trading Volumes Driven by Firm-specific News Releases?,* Ryan & Taffler (2002) explore the relationship between information flows of the capital markets, company trading volume activity and share price changes, comparing the impact that firm-specific information has on economically significant price changes and trading volume activity. The importance of a specific idiosyncratic news event is quantified by two different, yet complementary, metrics: (i) the number of times the different news event category triggers extraordinary price changes and trading activity (i.e., frequency), and (ii) the size of the price movements and trading volume activity triggered by the respective information releases (i.e., magnitude). The metrics are considered jointly to evaluate how essential investors view the conveyed news independent from how frequently they occur. The sample is based on firm-specific news on the 215 largest London Stock Exchange-listed entities for 1994 and 1995. Only economically significant market-adjusted returns and trading volumes are evaluated to eliminate the possibility of having random market activity affect the study's outcome.

Ryan & Taffler (2002) found that 65% of significant price changes and 63% of trading volume movements in the sample are explained by publicly available information, suggesting that ‘noise’ is not a significant factor in driving these movements. Out of all news categories examined, only a limited number of categories had prevalent explanatory power on what drove price changes and trading volume activity. Analysts’ recommendations and forecasts played the greatest role, closely followed by the firms’ formal accounting releases such as annual earnings and interim results. According to Ryan & Taffler (2002), the information generated by sell-side analysts could explain 17.4% of significant price changes and 16.1% of high trading volumes, while accounting releases explained 17.0% and 15.2%, respectively. Drawing from this, the authors cement the role of sell-side analysts as important information and value drivers. They find that the accounting releases dominate all other news releases when controlling for the relative release frequency. The implication is that accounting releases' role is not limited to confirming more timely news releases. The findings hold for whether the news conveyed is categorised as good or bad and conclude that the market does not anticipate a significant amount of information introduced in such accounting releases. As firm managers are served with managing analysts' expectations before accounting releases, analysts find price sensitive information to trade on before the known announcement date (Ryan & Taffler, 2002). The relationship between these two activities should help dwindle the level of surprise attached to the release of such information on the announcement date. Contrary to Ryan & Taffler's beliefs, accounting releases emerge as significant drivers to price movements and trading volumes.

3.3 Our contribution

The literature above highlights pre-existing works on the topic of sell-side research and its impact on stock prices and trading volume in various markets, in addition to outlining select theories within the fields of economics, finance, social sciences, and the intersections between them. Previous works on sell-side reports and their impacts provide a starting point for this paper.

We contribute to the literature by focusing on the Norwegian equity market, a market that has not been studied to the same degree as larger international markets, and we do this by examining the most liquid stocks found on the Oslo Stock Exchange, namely the OBX Index constituents. To the best of our knowledge, there have not been any previous studies investigating the relationship between Norwegian sell-side reports, stock returns, *and* trading volume on the Oslo Stock Exchange conducted prior to our study. However, some studies investigate the relationship between sell-side reports and stock returns for OBX Index constituents, such as Goksøyr & Grønn (2019). Our study complements not only pre-existing studies that investigate the relationship between sell-side research, stock returns and trading volume (e.g., Jegadeesh & Kim, 2006; Panchenko, 2007), but also those that investigate the relationship between sell-side research and stock returns (e.g., Sun et al., 2017; Su et al., 2018; Goksøyr & Grønn, 2019). A critical distinction between this paper and others that we have encountered is that we manually collected the data sample's sell-side reports. Thus, we run analyses on a data sample free from the overlap between report issuances, accounting figures- and firm-specific news releases. This distinction strengthens the validity of the research and results presented in this paper, as this paper solely focuses on the analyst reports without the noise that comes from firm-specific news and earnings announcements. We have not encountered any previous works utilising reports from the I/B/E/S database or similar databases that have explicitly stated that the sample is free of all overlapping events, except for a thesis written by Goksøyr & Grønn (2019) that controlled for firm-specific news when observing extreme anomalies. We find the method of removing ineligible observations, as seen in Goksøyr & Grønn (2019), flawed to some extent as we believe the sample is still contaminated with reports released in conjunction with lower-impact firm-specific news. We found that a large portion of the collected reports for our study was released in conjunction with firm-specific news, which we consider ineligible for the study, and we can only speculate what the proportion of such ineligible reports is in other studies.

Although the main objective of our study is not to directly test whether the Efficient Market Hypothesis holds on the Oslo Stock Exchange, it is important to note that any statistically significant results concerning abnormal returns would provide evidence against the semi-strong form of the EMH. Sell-side analysts take publicly available accounting figures and recent firm-specific news into their analyses and provide no new information to the market; hence there should be no anomalies if this form of the EMH holds[12].

[12] By employing two pricing models, we attempt to reduce the likelihood of selecting an inaccurate asset pricing model, but we do not circumvent the joint-hypothesis problem.

4. Hypotheses

This chapter presents four null hypotheses, with corresponding alternative hypotheses, examined through different data variables and hypothesis testing. This chapter is divided into two sections. Section 4.1 presents the tested hypotheses concerning stock returns, whereas Section 4.2 presents the hypotheses tested concerning trading volume. The hypotheses presented in this chapter are tested using test statistics, explained in greater detail in Section 6.

4.1 Hypotheses – stock returns

We examine two key variables, abnormal return and average abnormal return, to measure the incremental change to stock returns from the issuance of sell-side reports. The null- and alternative hypotheses presented below are interchangeable between abnormal return (AR) and average abnormal return (AAR).

(i) $$H_0: AR = 0 \; or \; AAR = 0$$

(ii) $$H_A: AR \neq 0 \; or \; AAR \neq 0$$

The null hypothesis (i) states that the (average) abnormal return equals zero, meaning that a specific (multiple) report(s) do(es) not generate a significant (average) abnormal return on the day of issuance. The alternative hypothesis (ii) states that the (average) abnormal return is not equal to zero, meaning that a specific (multiple) report(s) do(es) generate a significant abnormal return. Any rejection of the null hypothesis implies that the semi-strong form of the Efficient Market Hypothesis presented by Fama (1970) is violated. However, one should be careful to conclude that the EMH does not hold based on a few observations and give added weight to aggregated cross-sectional results.

4.2 Hypotheses – trading volume

To measure whether the sell-side reports in the sample affect trading volume, we use the variables abnormal volume (AV) and average abnormal volume (AAV). The hypotheses below are similar to those presented in Section 4.1, and as in the previous section, the two hypotheses are interchangeable between abnormal volume (AV) and average abnormal volume (AAV).

(iii) $H_0: AV = 0 \; or \; AAV = 0$

(iv) $H_A: AV \neq 0 \; or \; AAV \neq 0$

Similar to the hypotheses for stock returns, the null hypothesis (iii) states that the (average) abnormal volume is equal to zero, whereas the alternative hypothesis (iv) states that the (average) abnormal volume is not equal to zero. In other words, a sell-side report should not generate an abnormal volume if the null hypothesis holds. A rejection of the null hypothesis would imply increased investor recognition due to the sell-side report issuance based on the assumed relationship between investor recognition and trading volume.

5. Data collection and sample construction

This chapter outlines the data used for the analyses and is divided into three sections. In Section 5.1, the various sources used and variables obtained for our analysis is presented. Section 5.2 explains the steps to construct and prepare the dataset for the empirical studies. In Section 5.3, descriptive statistics of the data used is presented.

5.1 Data sources

We obtained the sell-side analyst reports from the online trading platform of a Norwegian operating investment bank. Daily returns and the trading volume[13] for the sample companies have been retrieved from Børsprosjektet, an online library created by the Norwegian School of Economics with compiled data for Oslo Stock Exchange-listed stocks dating back to 1980 (Børsprosjektet NHH, 2021). We have also retrieved the Fama French 3 factors (Fama & French, 1993) and the momentum factor (Carhart, 1997) from Kenneth R. French’s online data library (2021).

5.1.1 Sell-side analyst reports

As our analysis is heavily dependent on available and eligible sell-side analyst reports, our data gathering process started with the task of compiling these. Whereas most previous works we have encountered use the Institutional Broker’s Estimate System (I/B/E/S) or other costly data sources, we manually collected the sell-side reports for 23 out of the 25 sample companies dating back to the beginning of 2016[14]. The reports are from the online trading platform of a Norwegian operating investment bank, whose research offering[15] for the companies listed on the Oslo Stock Exchange is limited to traditional sell-side research. Having collected the reports manually, we omitted events that coincided with report issuances, such as the release of accounting numbers or firm-specific news. The number of research reports for each firm varies and is situational but includes reports sent out to clients in the event of firm-specific news, the release of accounting numbers, general recommendation updates, quarterly reviews and quarterly previews. The reports are attached with distinct features such as, but not limited

[13] Collected trading data includes data points for the fiscal years 2015 to, and including, 2020.
[14] Note that some companies have research coverage initiated after January 1st, 2016, for complete overview of the sample companies please see Appendix A.
[15] Research offering includes coverage of firms listed across multiple international stock exchanges, and is limited to traditional sell-side research for the Norwegian market.

to, a target price; a buy, hold or sell recommendation; and an earnings estimate. Descriptive statistics for the raw unfiltered and filtered sell-side report data set are presented in Section 5.3.

5.1.2 Stock returns and trading volume

Børsprosjektet is a financial database with daily and monthly stock data for companies that have been listed on the Oslo Stock Exchange between 1980 to 2020[16], in addition to other financial data such as future/forward and option prices. Børsprosjektet works similar to the CRSP database offered by WRDS (Wharton Research Data Services). We retrieved daily stock data for the sample companies for the dates between, and including, January 2nd of 2015 and November 27th of 2020. Børsprosjektet collects data directly from the Oslo Stock Exchange, which had its last independent operating day on November 27th of 2020 before merging with the Euronext system (Euronext, 2020), hence why December of 2020 is not included in the data sample.

For the selected period, we retrieved the variable *ReturnAdjGeneric*, which is the simple nominal return adjusted for dividend declaration, stock-splits and reverse-splits for each *SecurityId* (ticker). *ReturnAdjGeneric* uses the *Generic* variable as the basis for the calculation, reflecting the latest available daily stock price and overcoming the issue of unavailable stock prices on days without trading activity as observed when using the variable *LastPrice*. Furthermore, we retrieved the variables *OffShareTurnover* and *SharesIssued* for the official number of shares traded and the total number of shares outstanding at a specific date. Descriptive statistics for the data collected from Børsprosjektet is presented in Section 5.3.

5.1.3 Fama French factors and Carhart momentum factor

The Fama French- and Carhart Momentum factors are obtained from the Kenneth R. French Data Library (2021). We obtain the Fama French European 3 Factors, using the Western European region's value-weighted portfolio less the U.S. one month T-bill rate as the basis for the factors. We find these factors to be more appropriate for our analysis to reflect the overall market sentiment on the Oslo Stock Exchange than the default factors based on the US stock

[16] At the time of writing this thesis, Børsprosjektet does not have available data points after 27 November 2020.

market. Further explanation of the Fama French factors and the Carhart momentum factor is explained in Section 6, including their application in the empirical study.

5.2 Constructing the dataset

The data sample is restricted to sell-side reports for 2016 to 2020, including six years of daily stock prices and factor data (Fama French factors and momentum factor) as we use data for 2015 to estimate the necessary variables for the empirical study. We have chosen a time frame of 5 years to ensure sufficient eligible sell-side reports for the sample companies. For our dataset, we manually entered the issuance date of each report, the type of report (e.g., quarterly preview), target price, price at the time of publishment, recommendation type (buy/sell/hold) and the name(s) of the analyst(s) behind the respective reports.

Once we had a complete raw set of analyst reports, we limited the dataset to exclude report issuances that coincide with firm-specific news and earnings announcements. This exclusion was done to avoid Type I errors, in other words finding statistical evidence for a sell-side report released in conjunction with firm-specific news where the anomaly is driven by the news and not the issuance of the report. Additionally, we have adjusted the dates of reports released on non-trading days (i.e., holidays or weekends) to be effective the first trading day following the publishment of the report.

5.3 Descriptive statistics

For our analysis, we collected and examined a sample of 1,319 sell-side reports for 23 out of the 25 OBX constituents (five large-cap, fifteen mid-cap, three small-cap[17]). After filtering the recommendations conditional on their eligibility as described in Section 5.2, we reduced the dataset to 477 eligible sell-side reports. The first sample recommendation for all companies occurred in Q4 2015[18], except for ENTRA.NO, AKER.NO, NEL.NO and TOM.NO, which were observed in June 2016; December 2017; December 2019; and October 2020, respectively, following the brokerage's initiation of coverage report (IoC). Consult *Table 1*

[17] We define large cap companies as having a total market capitalisation of over $10 billion; mid cap between $2 and $10 billion; and small cap below $2 billion. Market caps are calculated as of December 2020. A NOK/USD rate of 8.7 has been applied for currency conversion.
[18] Sample of 1319 sell-side reports. Only reports issued after 31 December 2015 included in the sample of 477 reports, however one report per sample company issued prior to 31 December 2015 is used to establish the change in recommendation.

below or *Table A.1* in *Appendix A* for a complete list of companies included in the sample. The percentage of buy, hold and sell recommendations are calculated based on the number of eligible reports. For the sample period (2016 – 2020), 64% of the sell-side reports were buy recommendations, 29% hold, and 7% were sell recommendations. The year in which most eligible recommendations occurred was 2016 (126), followed by 2017 (102). The years 2018 and 2020 had the same number of eligible reports (90), while 2019 had the fewest eligible observations (69). The 23 individual companies belong to 16 distinct industry groups. The most common was the Seafood sector (4), followed by Oil Services, Power and Renewable, Insurance, and E&P (2 companies each).

Table 1: Descriptive Statistics: Data Sample of Analyst Recommendations

This table presents high-level statistics for the sell-side analyst recommendations used for the study. The table shows the number of total reports in the entire data set (Total), the number of reports deemed eligible for the event studies (Eligible Reports), the percentage of reports issued belonging to the various rating categories (Buy, Hold and Sell) as well as the number of eligible reports per year (Reports Per Year) for each company.

	Number of Reports		Percentage of Reports			Reports Per Year				
Company ticker	Total	Eligible Reports	Buy	Hold	Sell	2016	2017	2018	2019	2020
AKSO.NO	46	24	71%	29%	0%	5	6	6	4	3
ENTRA.NO	20	10	50%	40%	10%	3	4	1	0	2
SCATC.NO	32	23	87%	9%	4%	8	5	7	2	1
GJF.NO	72	26	23%	77%	0%	7	5	5	5	4
AKRBP.NO	59	28	89%	11%	0%	8	3	6	5	6
SALM.NO	45	22	64%	32%	5%	3	8	2	5	4
AKER.NO	16	9	100%	0%	0%	0	1	4	2	2
YAR.NO	76	37	100%	0%	0%	8	7	7	7	8
RECSI.NO	27	15	33%	67%	0%	5	5	3	0	2
EQNR.NO	73	34	85%	6%	9%	8	7	8	7	4
NEL.NO	25	7	0%	0%	100%	0	0	0	1	6
TEL.NO	123	20	0%	70%	30%	6	6	5	2	1
DNBH.NO	76	31	100%	0%	0%	10	8	4	5	4
TOM.NO	3	2	0%	0%	100%	0	0	0	0	2
NHY.NO	106	33	39%	42%	18%	9	5	4	6	9
ORK.NO	70	22	14%	73%	14%	4	5	4	4	5
LSG.NO	55	6	100%	0%	0%	3	0	0	1	2
TGS.NO	51	21	81%	19%	0%	4	5	5	3	4
NOD.NO	65	27	78%	19%	4%	7	6	7	0	7
MOWI.NO	82	22	64%	36%	0%	8	3	4	3	4
STB.NO	74	28	46%	54%	0%	10	6	4	4	4
SUBC.NO	55	21	86%	14%	0%	6	4	3	3	5
BAKKA.NO	68	9	44%	33%	22%	4	3	1	0	1
Total	1319	477	64%	29%	7%	126	102	90	69	90

Over the sample period, the 23 companies' stocks saw an average annualised return of 18.3%. The most profitable individual stock of the index was NEL, which saw an annualised return of 55.4% over the five years. The most profitable year for investors in the sample companies was 2016, with a value-weighted average return of 43.6% for the OBX Index. Following the

SMB factor in the Fama French Model, small-cap stocks (23.1%) outperformed large-cap stocks (13.0%) by 10.1% on average over the five-year sample period, while mid-cap stocks generated the highest average returns (31.5%)[19]. However, these findings are only consistent with the Fama French SMB factor when using arithmetic returns, and large-cap stocks (8.7%) significantly outperformed small-cap stocks (0.4%) when using value-weighted[20] annualised returns.

See *Table B.1* in *Appendix B* for return data on the sample companies. See *Figure B.1* in *Appendix B* for cumulative value-weighted development of the various market capitalisation-based categories.

[19] Average of YoY return.
[20] Value-weighted within each respective category

6. Methodology

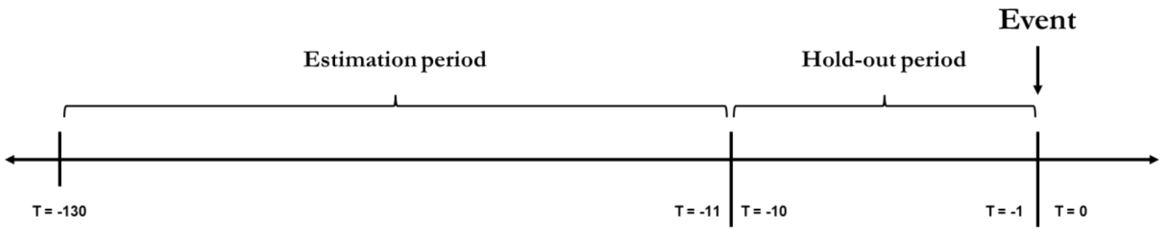
This chapter outlines the methodology used for the analyses in the study. We apply a deductive approach for our studies, meaning that we base our analysis on existing frameworks and apply those to our hypotheses.

6.1 Event study

We employ the event study methodology to measure stock returns and trading volume reactions to the recommendations. The main objective of the event study is to isolate any incremental changes to the securities' prices as a result of the sell-side report issuance. Each recommendation, also referred to as an event, has been assigned *t=0* for the publication date[21]. This study is designed with an estimation period from *t-130* to *t-11*, a hold-out period from *t-10* to *t-1* and the event window as a one-day event occurring at *t=0*. The estimation window's duration is defined as 120 days per MacKinlay's (1997) recommended practice for event studies, providing a sufficiently large sample with low intertemporal correlation. The hold-out period is included to prevent contamination of the sample in the event of information leakage about the upcoming release of reports, as noted in Lidén (2007). A visual presentation of the event study timeline can be observed below in Figure 1.

Figure 1: Event study timeline with a 10-day hold-out period

The timeline includes an estimation period of 120 days, from t-130 to t-11 days before the event, a hold-out period of 10 days, from t-10 to t-1 day(s) before the event and the event at t=0. The estimation period is the basis for calculating expected returns and the variance of abnormal returns.



We use the same event study characteristics to measure incremental changes to stock returns and trading volume; however, we employ different methodologies to measure and detect these changes. To determine whether there is a reaction in stock returns, we measure abnormal return as the difference between realised return and expected return, obtained using the *Fama French Three-Factor Model* and the *Carhart Four-Factor Model*. Similarly, for measuring

[21] As stated in Section 5, reports published on non-trading days are assigned t=0 on the first following trading day.

reactions to trading volume, we employ the *Adjusted-Mean Model* and the *Market Model* to calculate the expected trading volume and then find the abnormal volume by the difference between the expected trading volume and the realised trading volume. When calculating the abnormal volume, we log-transform the percentage of shares traded to the number of outstanding shares. To test for significance for each event, we use the *Student's T-Test*, commonly referred to as the *T-Test*, to determine whether the variables are statistically significant. Additionally, we perform a cross-sectional significance test of the aggregated variables using the *Cross-Sectional T-Test*.

6.2 Model specifications – abnormal return

The realised daily returns for each stock have been retrieved directly from Børsprosjektet (2021). However, the returns retrieved from Børsprosjektet can be calculated as shown in equation 6.1, after applying an adjustment factor where necessary:

$$R_{i,t} = \frac{Closing\ price_{i,t} - Closing\ price_{i,t-1}}{Closing\ price_{i,t-1}} \quad \textbf{(6.1)}$$

Realised returns are used in conjunction with the expected returns to calculate the abnormal returns. This paper uses simple arithmetic returns as defined in equation (6.1). Hudson & Gregoriou (2015) notes that one should calculate returns as either arithmetic or logarithmic returns for best practice, yet neither approach is superior to the other. We have opted to use arithmetic returns, although previous studies such as Jegadeesh & Kim (2006) and Goksøyr & Grønn (2019) utilise logarithmic returns, we do not find this to be an obstacle for comparing results.

We describe the different methods for calculating expected- and abnormal returns in the following subsections.

6.2.1 Expected return

Many different models calculate expected returns used to establish a baseline return for a security. Asset pricing models are well-studied in finance, yet there is not necessarily one correct model to apply. The Capital Asset Pricing Model (Sharpe, 1964; Lintner, 1965; Mossin, 1966), known as CAPM, was the first framework developed to answer how an investment's risk affects the pricing of said investment (Perold, 2004). The CAPM has been thoroughly tested and discredited due to numerous anomalies (Eckbo, 2009). To calculate expected returns in this study, we use the Fama French Three-Factor- and the Carhart Four-Factor model. The Fama French Three-Factor- and Carhart Four-Factor models are extensions of the CAPM, and they attempt to capture variation in stock prices through extending the CAPM with additional factors. This subsection covers the basics of the models and their relevance.

Fama French Three-Factor Model

The Fama French Three-Factor Model extends on the CAPM by using the existing market factor and introducing two firm-specific risk factors that are believed to capture the variation in stock prices more accurately: SMB (Small Minus Big) and HML (High Minus Low)[22]. Like other asset pricing models and factors discovered, the SMB and HML factors are determined on an ex-post basis of stock returns. The SMB factor measures the additional return an investor has historically earned by investing in a security with a small market capitalisation, also known as the "size premium". The HML factor measures the additional return an investor has historically earned by investing in securities of firms with high book-to-market value, also known as the "value premium".

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{MKT} * \left(MKT_t - R_{f,t}\right) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \varepsilon_{i,t} \qquad \textbf{(6.2)}$$

Description of the variables used in the Fama French 3-Factor Model:

$R_{i,t} - R_{f,t}$	Return for security *i* in excess of the risk-free rate at time *t*
α_t	Intercept/alpha at time *t*
β_{MKT}	Exposure to the market factor (market beta)
$MKT_t - R_{f,t}$	Market return in excess of the risk-free rate at time *t*
β_{SMB}	Exposure to the SMB factor
SMB_t	"Size premium" factor at time *t*
β_{HML}	Exposure to the HML factor
HML_t	"Value premium" factor at time *t*
ε_t	Error term at time *t*

[22] See Kenneth R. French's online library for methodology behind factors.

Carhart Four-Factor Model

The Carhart Four-Factor Model elaborates on the Fama French Three-Factor Model by adding a momentum factor, a variable based on the notion that securities with strong past performance continue to outperform those with poor performance. The additional momentum factor has contributed to the Carhart Four-Factor Model's rising popularity.

$$R_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{MKT} * \left(MKT_t - R_{f,t}\right) + \beta_{SMB} * SMB_t + \beta_{HML} * HML_t + \beta_{WML} * WML_t + \varepsilon_{i,t} \quad \textbf{(6.3)}$$

Description of variables unique to the Carhart Four-Factor Model:

β_{WML}	Exposure to the momentum factor
WML_t	Momentum factor at time *t*

6.2.2 Abnormal return

We use both abnormal return (AR) and average abnormal return (AAR) in this study. AR is used to study individual events, whereas AAR is used when examining the effect of sell-side reports on an aggregate and cross-sectional basis at the same point in time (t=0).

Abnormal return (AR)

To estimate the abnormal return (AR) for each security *i*, at time *t*, the Fama French Three-Factor Model and the Carhart Four-Factor Model were used. The AR estimate for security *i* at time *t* is calculated as realised returns in excess of the risk-free rate at time t less the expected return in excess of risk-free at time t as calculated by respective asset pricing models:

$$AR_{i,t} = (R_{i,t} - R_{f,t}) - (E\left(R_{i,t} \middle| X_t\right) - R_{f,t}) \quad \textbf{(6.4)}$$

Description of variables used in calculating AR:

$R_{i,t} - R_{f,t}$	Realised return in excess of the risk-free rate for security *i* at time *t*
$E\left(R_{i,t} \middle| X_t\right) - R_{f,t}$	Expected return in excess of the risk-free rate for security *i* at time *t*

Average abnormal return (AAR)

As our study focuses on the incremental change in stock returns on the day of report issuance, we compute the AAR to get a sense of the aggregated effect of multiple reports. The AAR is the average abnormal return of *N* reports at time *t*:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \qquad \textbf{(6.5)}$$

6.3 Model specifications – abnormal volume

As done in the analyses of abnormal return, the abnormal volume analyses compare realised trading volume to expected trading volume through different frameworks. This section covers the transformation of raw trading volume to a log-transformed percentage of shares outstanding, the use of mean-adjusted trading volume and ordinary least squares (OLS) regression market model for establishing expected trading volume, and the calculation of abnormal volume and average abnormal volume measures.

6.3.1 Measure of trading volume

In determining a securities trading volume, we use the log-transformed percentage of shares outstanding as used by Cready and Ramanan (1991), who documents the importance of log-transforming raw trading volumes for empirical studies. Before taking the natural log of shares outstanding, a constant of 0.000255 is added to the calculation to prevent taking the natural log of zero. This formula to calculate the trading volume, for security *i* at time *t*, is used by Cready and Ramanan (1991) and Campbell and Wasley (1996) in their studies:

$$V_{i,t} = \log\left(\frac{n_{i,t} * 100}{S_{i,t}} + 0.000255\right) \qquad \textbf{(6.6)}$$

Description of variables used in calculating log-transformed trading volume:

$n_{i,t}$	Number of shares traded for security *i* at time *t*
$S_{i,t}$	Total number of shares outstanding for security *i* at time *t*

6.3.2 Expected trading volume

This study uses mean-adjusted trading volume and an OLS market model regression to estimate the expected trading volume for security *i* at time *t*. As with the asset pricing models described in Section 6.2, there is no clear consensus on the superior model; hence we employ two models separately to estimate the expected trading volume.

Mean-Adjusted trading volume

The mean-adjusted trading volume is a straight-forward and simple process and is calculated by the average trading volume (see subsection 6.3.1 for trading volume measure) for security *i* during the estimation period leading up to the event at time *t*:

$$\bar{V}_i = \frac{1}{T}\sum_{t=f}^{t=l} V_{i,t} \qquad \textbf{(6.7)}$$

Description of variables used in calculating the mean-adjusted trading volume:

$V_{i,t}$	Actual trading volume for security *i* at time *t*
f	First day in the estimation period
l	Last day in the estimation period

Ordinary Least Squares Market Model

The second method for calculating expected trading volume is through the Market Model, using an OLS regression to obtain α_i and β_i. The market model calculates the expected trading volume for security *i* at time *t* with regards to the overall market trading volume. For this study, we use the OBX Index constituents as a proxy for the market (MKT):

$$E[V_{i,t}] = \alpha_i + \beta_i * V_{MKT} \qquad \textbf{(6.8)}$$

where

$$V_{MKT} = \frac{1}{N}\sum_{i=1}^{N} V_{i,t} \qquad \textbf{(6.9)}$$

6.3.3 Abnormal trading volume

Abnormal volume

Calculated similar to abnormal returns, abnormal volume is calculated as realised trading volume less expected trading volume. Equation 6.10 shows the mean-adjusted abnormal trading volume, whereas equation 6.11 shows the market model abnormal trading volume:

Mean-Adjusted abnormal trading volume:

$$v_{i,t} = V_{i,t} - \bar{V}_i \qquad \textbf{(6.10)}$$

Market Model abnormal trading volume:

$$v_{i,t} = V_{i,t} - E\left[V_{i,t}\right] \quad \textbf{(6.11)}$$

Average abnormal volume

Like the AAR calculation, we aggregate the results from the individual level events to gain a better understanding of the incremental changes to trading volumes by calculating the average abnormal volume for *N* reports at time *t*:

$$AAV_t = \frac{1}{N}\sum_{i=1}^{N} v_{i,t} \quad \textbf{(6.12)}$$

Interpretation of the measure of trading volume

We convert the abnormal volume values to a percentage change for results that are easier to convey and interpret. The conversion formula is found in equation 6.13 and converts the difference between the natural log of realised percentage shares traded and the natural log of expected percentage shares traded to a percentage difference between those. The value after the conversion is only used as a table output and is not used for hypothesis testing.

$$AV_{converted} = e^{v_{i,t}} - 1 \quad \textbf{(6.13)}$$

The same calculation, although different input parameters are used to convert the average abnormal volume results:

$$AAV_{converted} = e^{AAV_t} - 1 \quad \textbf{(6.14)}$$

6.4 Test statistics

Two different parametric test statistics with different applications (i.e., individual events versus a sample of events) have been used for hypothesis testing. These tests have been employed to assess whether or not the abnormal returns, average abnormal returns, abnormal volumes, and average abnormal volumes for the chosen securities at the various event dates are significantly different from zero. These tests are performed across the expected return (asset pricing) and expected volume models used in this study, and they are subject to null and alternative hypotheses, H_0 and H_A, as described in Section 4. Although previous research (e.g., Fama, 1976) argues for non-parametric test statistics when analysing stock returns, we have opted to solely use parametric statistics as we find the distribution of returns to display limited skewness, yet some higher kurtosis than the Gaussian distribution. Similarly, we find the natural-log transformed trading volumes to approach a normal distribution, although slight skewness, and we have determined that the distribution characteristics allows for using the t-test and the cross-sectional t-test. This is consistent with previous research (e.g., Cready & Ramanan, 1991), finding the natural-log transformation to provide a sample closer to normality than raw trading volumes. See *Appendix C* for a visual presentation of the frequency distribution of stock returns and log-transformed trading volume.

6.4.1 T-Test

The t-test provides a test statistic for investigating individual securities *i* at time *t*. This study focuses on the incremental changes in stock returns and trading volume at the day of a stock recommendation issuance, and the application of the t-test assumes that the abnormal returns follow the Student's t-distribution. Given the hypotheses presented in Section 4, the t-test applied is a two-tailed one, testing at the 95% confidence interval. Although the calculations for significance testing of the abnormal returns and the abnormal volumes are close to identical, both formulas are presented in this subsection to avoid misinterpretation.

The formula for the test statistic for abnormal return for security *i* at time *t* is given by:

$$t_{AR_{i,t}} = \frac{AR_{i,t}}{S_{AR_i}} \tag{6.15}$$

where S_{AR_i} is the standard deviation of the abnormal returns for security *i* during the estimation period and is the square root of the variance:

$$S_{AR_i}^2 = \frac{1}{M_i - k} \sum_{t=T_0}^{T_1} (AR_{i,t})^2 \tag{6.16}$$

The variance of abnormal return is calculated as the sum of squared abnormal returns from T_0, the first day in the estimation period, to T_1, the last day in the estimation period. This sum is divided by the number of matched observations (M_i) less k, the number of parameters needed to compute the abnormal returns. In the case of the Fama French Three-Factor Model, this is equivalent to $k = 4$ (one constant and three factors) and $k = 5$ when applying the Carhart Four-Factor Model.

Similarly, the test statistic for significance testing of abnormal volume uses a near-identical formula to the one corresponding to abnormal return (equation 6.15); however, the input variable is the abnormal volume (AV) rather than abnormal return (AR):

$$t_{AV_{i,t}} = \frac{AV_{i,t}}{S_{AV_i}} \quad \textbf{(6.17)}$$

The variance calculation for abnormal volume features the same formula with replaced input variable:

$$S_{AV_i}^2 = \frac{1}{M_i - k} \sum_{t=T_0}^{T_1} (AV_{i,t})^2 \quad \textbf{(6.18)}$$

For the mean-adjusted model, $k = 1$, and $k = 2$ when applying the market model.

6.4.2 Cross-Sectional T-Test

The cross-sectional test is used to analyse the aggregate incremental change in stock returns and trading volume across multiple securities at time *t*. The cross-sectional test was introduced by Brown and Warner (1980, 1985) and is frequently used in event studies. Like the t-test, the same assumption about normality in the distribution of AR must be valid. Disputing evidence presented by Fama (1976) about non-normality in daily stock returns, Brown and Warner (1985) argues that the Central-Limit Theorem (CLT) dictates that the distribution of sample average abnormal returns converges to a normal distribution if the cross-section of securities is independent and identically distributed (I.I.D). The cross-sectional test for hypothesis testing of AAR is given by:

$$t_{AAR_t} = \sqrt{N} \frac{AAR_t}{S_{AAR_t}} \quad \textbf{(6.19)}$$

where N is the number of observations, and S_{AAR_t} is the standard deviation across N firms at time *t* and is the square root of the variance:

$$S_{AAR_t}^2 = \frac{1}{N-1} \sum_{i=1}^{N} (AR_{i,t} - AAR_t)^2 \quad \textbf{(6.20)}$$

As with the t-test for individual events, the difference between the calculations for abnormal returns and abnormal volume comes down to the input variables:

$$t_{AAV_t} = \sqrt{N} \frac{AAV_t}{S_{AAV_t}} \quad \textbf{(6.21)}$$

where S_{AAV_t} is given by:

$$S_{AAV_t}^2 = \frac{1}{N-1} \sum_{i=1}^{N} (AV_{i,t} - AAV_t)^2 \quad \textbf{(6.22)}$$

7. Results and key findings

This chapter presents the results of the analyses conducted. The study can be broadly divided into event studies on abnormal return and event studies on abnormal volume. Both the studies on abnormal return and abnormal volume are examined in detail on an aggregate and individual basis. This chapter is divided into three sections to convey the results as clearly as possible, detailing the results from the event studies based on different self-imposed criteria and characteristics. Firstly, Section 7.1 presents the results from the significance tests of average abnormal return and average abnormal volume for various sell-side report characteristics (Tables 2 and 3). Secondly, Section 7.2 presents the results from the significance tests of average abnormal return and average abnormal volume for the sample companies (Tables 3 and 4). Lastly, Section 7.3 presents summarised statistics from significance tests of each event (see Tables 6 and 7).

7.1 Aggregated results for report characteristics

This section presents the results from analysing the impact of sell-side reports on the sample companies by significance testing of average abnormal return and average abnormal volume for various report characteristics by using the test statistics outlined in Section 6.4 for hypothesis testing, allowing to identify statistically significant anomalies based on the various report characteristics.

The results from the average abnormal return study, presented in Table 2, show similarities between the application of the Fama French Three-Factor Model and the Carhart Four-Factor Model. For both models, we find that when a recommendation is upgraded or downgraded, a stock experiences a statistically significant abnormal return on that day. Using the Fama French Three-Factor Model, we find that a stock experiences an average abnormal return of 2.04% on the day of an upgrade and an average abnormal return of -0.87% on the day of a downgrade. The Carhart Four-Factor Model provides similar results, with a 2.08% average abnormal return on days of an upgrade and an average abnormal return of -0.85% on days of a downgrade. The average abnormal return observed on the day of an upgrade is close to that Jegadeesh & Kim (2006) found for upgraded recommendations in the US market of 1.76%, a greater anomaly than those found in the other G7 markets. However, the average abnormal return for the OBX Index constituents on days of downgrades is significantly lower than what was found for the US market (-3.19%) and closer to that of the other G7 market, ranging from -0.09% to -0.45% (Jegadeesh & Kim, 2006). Furthermore, we find that both models provide a statistically significant average abnormal return when a recommendation is issued with a downwards revised target price between 0% to 10%. This average abnormal return is measured to -0.68% with both asset pricing models.

Table 2: Average Abnormal Return Event Study for Different Report Characteristics

This table presents the average abnormal returns for various sell-side analyst report characteristics, using the Fama French Three-Factor Model (FF3) and the Carhart Four-Factor Model (Carhart). T-values accompany the average abnormal returns for the various characteristics and a column displaying whether it is significant or not at the 5% level (using a two-tailed cross-sectional t-test with 5% level at an absolute value greater than or equal to 1.96) and if we can reject the null hypothesis, H_0 in favour of the alternative, H_A. Report characteristics explored are purchase recommendation, recommendation change, change in target price, recommendation type and recommendation year.

	Observations	FF3			Carhart		
	Number of observations	Average Abnormal Return	T-stat	Significant at 5% level (Y/N)	Average Abnormal Return	T-stat	Significant at 5% level (Y/N)
Purchase recommendation							
Buy	307	0.19%	1.01	N	0.19%	1.01	N
Hold	137	(0.06%)	(0.23)	N	(0.04%)	(0.16)	N
Sell	33	0.02%	0.03	N	0.09%	0.16	N
Recommendation change							
Upgrade	39	2.04%	2.29	Y	2.08%	2.37	Y
Downgrade	38	(0.87%)	(2.46)	Y	(0.85%)	(2.63)	Y
No change	400	0.01%	0.07	N	0.01%	0.10	N
Δ Target price							
>15%	33	1.05%	1.55	N	1.06%	1.59	N
<15% | >10%	14	0.82%	1.61	N	0.87%	1.55	N
<10% | >0%	82	0.14%	0.55	N	0.16%	0.60	N
No change	252	0.22%	1.03	N	0.22%	1.07	N
<0% | > (10%)	66	(0.68%)	(2.20)	Y	(0.68%)	(2.22)	Y
<(10%) | >(15%)	10	0.29%	0.22	N	0.45%	0.34	N
<(15%)	20	(1.02%)	(1.20)	N	(1.08%)	(1.22)	N
Recommendation type							
Quarterly Preview	226	(0.01%)	(0.11)	N	(0.03%)	(0.23)	N
Quarterly Review	115	0.09%	0.31	N	0.11%	0.37	N
Update	116	0.08%	0.21	N	0.10%	0.00	N
Recommendation year							
2016	126	(0.10%)	(0.33)	N	(0.05%)	(0.21)	N
2017	102	0.09%	0.54	N	0.09%	0.46	N
2018	90	(0.12%)	(0.44)	N	(0.13%)	(0.31)	N
2019	69	0.06%	0.13	N	0.06%	0.26	N
2020	90	0.67%	1.44	N	0.66%	1.43	N

For the abnormal average volume study on these characteristics, as displayed in Table 3, it is evident that reports generate abnormal volume if having the right report characteristics. As with the average abnormal returns presented in Table 2, the two methods of calculating expected volume have few differences. Both models result in statistically significant anomalies for most purchase recommendations, recommendation changes, recommendation types, recommendation years, with a few more discrepancies observed for changes in target price.

Table 3: Average Abnormal Volume Event Study for Different Report Characteristics

Using the Mean-Adjusted Model and Market Model, this table presents the average abnormal volume for various sell-side analyst report characteristics. T-values accompany the average abnormal volume for the various characteristics and a column displaying whether it is significant or not at the 5% level (using a two-tailed cross-sectional t-test with 5% level at an absolute value greater than or equal to 1.96) and if we can reject the null hypothesis, H_0 in favour of the alternative, H_A. Report characteristics explored are purchase recommendation, recommendation change, change in target price, recommendation type and recommendation year.

	Observations	Mean-Adjusted Model			Market Model		
	Number of observations	Average Abnormal Volume	T-stat	Significant at 5% level (Y/N)	Average Abnormal Volume	T-stat	Significant at 5% level (Y/N)
Purchase recommendation							
Buy	307	24.24%	7.20	Y	24.22%	7.54	Y
Hold	137	24.51%	4.60	Y	17.02%	1.92	N
Sell	33	18.88%	1.66	N	16.60%	3.42	Y
Recommendation change							
Upgrade	39	47.34%	4.21	Y	49.01%	4.33	Y
Downgrade	38	39.83%	3.73	Y	35.13%	3.53	Y
No change	400	20.48%	6.99	Y	17.88%	6.66	Y
Recommendation type							
Quarterly Preview	226	4.48%	1.41	N	2.49%	0.83	N
Quarterly Review	115	58.67%	10.54	Y	53.14%	10.44	Y
Update	116	34.22%	5.04	Y	33.29%	5.37	Y
Δ Target price							
>15%	33	27.34%	2.13	Y	20.08%	1.79	N
<15% | >10%	14	12.97%	1.03	N	8.67%	0.99	N
<10% | >0%	82	23.20%	3.29	Y	21.86%	3.21	Y
No change	252	18.78%	5.49	Y	17.66%	5.51	Y
<0% | > (10%)	66	37.64%	4.36	Y	37.81%	4.39	Y
<(10%) | >(15%)	10	16.62%	0.76	N	(0.92%)	(0.09)	N
<(15%)	20	61.52%	4.33	Y	44.38%	3.89	Y
Recommendation year							
2016	126	30.80%	6.08	Y	25.66%	5.35	Y
2017	102	17.02%	3.21	Y	18.75%	3.49	Y
2018	90	33.02%	5.05	Y	21.29%	3.60	Y
2019	69	5.10%	0.92	N	7.93%	1.43	N
2020	90	29.69%	3.61	Y	30.36%	4.27	Y

The Mean-Adjusted Model results show that hold recommendations generated the highest average abnormal volume among the purchase recommendations with 24.51% average abnormal volume. For the Market Model results, hold recommendations did not generate statistically significant average abnormal volume and buy recommendations created an average abnormal volume of 24.22% versus sell recommendations that created an average abnormal volume of 16.60%. Furthermore, we find that target price revisions between 10% and 15% (absolute value) generate no statistically significant average abnormal volume using either model. We also find statistically significant average abnormal volume for revisions greater than 15% (absolute value) using the Mean-Adjusted Model. The Market Model finds no statistical significance for upwards revisions greater than 15%. We find statistically significant average abnormal volume for Quarterly Reviews and Updates, yet no statistically significant result for Quarterly Previews.

Interestingly, the reports did not generate a statistically significant average abnormal volume for 2019. Factors behind this are unclear but may be correlated with the fact that 2019 has the least eligible reports in the sample. Contrary to the findings of Jegadeesh & Kim (2006), we find upgraded recommendations to result in the largest anomalies, whereas they found downgraded recommendations to generate a trading volume of 37.72%[23] larger than that of an upgraded revision in the US. Jegadeesh & Kim (2006) used standardised trading volume for the 20 days prior and 20 days after the event date as the basis for the standardised trading volume, so a direct comparison of results is not warranted.

7.2 Aggregated results for sample companies

This section details the results from estimating average abnormal return (AAR) and average abnormal volume (AAV) for each sample company. By calculating the AAR and AAV, we can evaluate the extent of the report's effects on a higher level. As in Section 7.1, results are first presented for the event study using stock returns, then the event study using trading volume.

As depicted in Table 4, only reports for 3 out of the 23 sample companies yield any statistical significance at the 5% level when comparing realised returns to those modelled by the Fama French Three-Factor Model. This number is lowered to 2 out of the 23 sample companies with the Carhart Four-Factor Model. It should be noted that Tomra Systems (TOM.NO) is one of these 3 (2) companies and should be disregarded on an individual level[24] due to the low sample size. Given that most companies have non-significant test statistics, it may come as a surprise that 2 (1) companies (excluding TOM.NO) experience significant average abnormal returns for the given events. However, we believe that the statistically significant values for these companies are statistically sound due to the relatively large sample sizes for NOD.NO and STB.NO, and the interesting findings may, hypothetically, be explained by the investment

[23] Standardised trading volume of 2.3 versus 1.67
[24] Tomra Systems is included for significance testing of the total sample size.

bank having a stronger position in the FIG and Hardware & Equipment space both reputational- and investor basis wise.

From the results using the Fama French Three-Factor Model, we observe that for the 27 eligible reports for Nordic Semiconductor (NOD.NO), the stock experiences an average abnormal return of -1.92% on the day of issuance, and the anomalies are on average -1.94% on the day of issuance when applying the Carhart Four-Factor Model. Storebrand (STB.NO), on the contrary, experienced a statistically significant positive average abnormal return of 0.80% on the days of issuance of the sample size of 28 reports, using the Fama French Three-Factor Model. We find these results interesting as Nordic Semiconductor (78%) has a larger share of buy recommendations than Storebrand (46%). The results were not significant when employing the Carhart Four-Factor Model. Furthermore, the results were not statistically significant for the sample companies as a collective group using either model.

Table 4: Average Abnormal Return Event Study Results

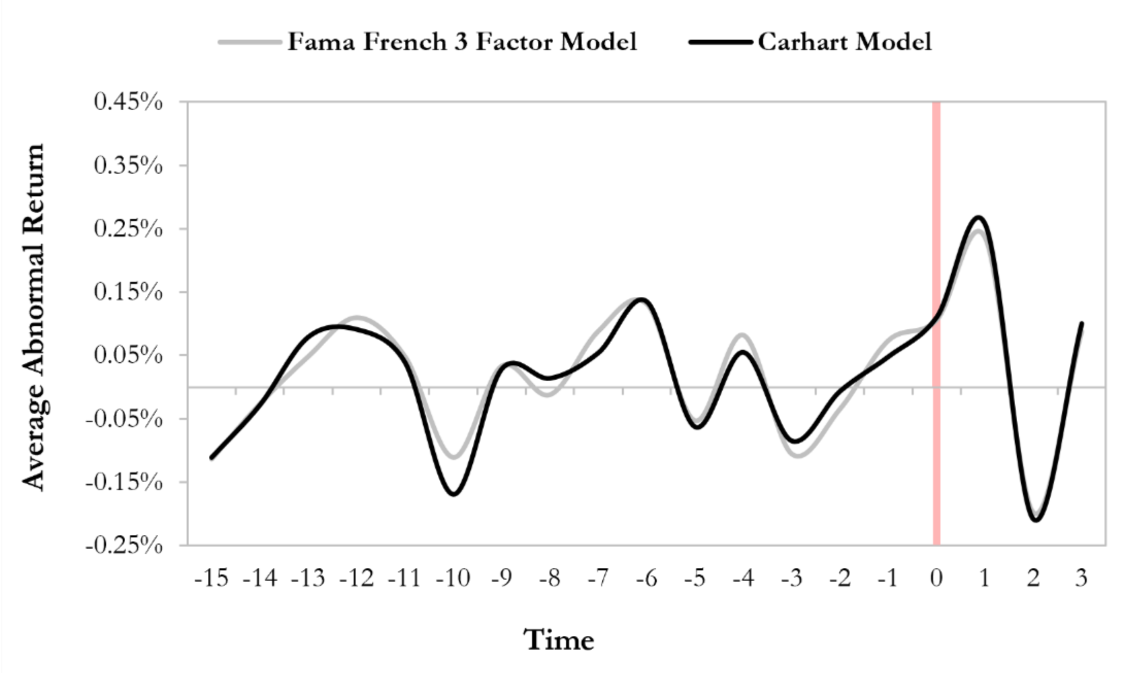
This table presents the average abnormal return for each sample company. Each sample company is examined using the Fama French Three-Factor Model (FF3) and the Carhart Four-Factor Model (Carhart) to determine the average abnormal return, then tested using a two-tailed cross-sectional t-test. For each model, the average abnormal return is presented, along with the corresponding t-values and a column showing whether the average abnormal return is significant at the 5% level for each sample company and if we can reject the null hypothesis, H_0 in favour of the alternative, H_A.

	FF3			**Carhart**		
Company ticker	Average Abnormal Return	T-stat	Significant at 5% level (Y/N)	Average Abnormal Return	T-stat	Significant at 5% level (Y/N)
AKSO.NO	0.08%	0.18	N	0.14%	0.33	N
ENTRA.NO	1.85%	0.97	N	1.86%	0.97	N
SCATC.NO	(0.45%)	(0.56)	N	(0.47%)	(0.58)	N
GJF.NO	(0.03%)	(0.14)	N	0.00%	0.01	N
AKRBP.NO	0.51%	0.90	N	0.48%	0.93	N
SALM.NO	0.08%	0.19	N	0.01%	0.02	N
AKER.NO	1.42%	1.53	N	1.49%	1.66	N
YAR.NO	0.01%	0.02	N	0.03%	0.08	N
RECSI.NO	3.12%	1.38	N	3.04%	1.35	N
EQNR.NO	(0.08%)	(0.23)	N	(0.08%)	(0.25)	N
NEL.NO	1.59%	0.69	N	1.65%	0.72	N
TEL.NO	(0.41%)	(1.67)	N	(0.40%)	(1.61)	N
DNBH.NO	0.14%	0.49	N	0.16%	0.58	N
TOM.NO[1]	(0.26%)	(3.21)	Y	(0.26%)	(3.48)	Y
NHY.NO	(0.40%)	(0.86)	N	(0.25%)	(0.58)	N
ORK.NO	(0.15%)	(0.70)	N	(0.24%)	(1.13)	N
LSG.NO	0.84%	1.32	N	0.89%	1.40	N
TGS.NO	0.58%	0.73	N	0.69%	0.87	N
NOD.NO	(1.92%)	(1.99)	Y	(1.94%)	(2.02)	Y
MOWI.NO	(0.37%)	(0.88)	N	(0.36%)	(0.88)	N
STB.NO	0.80%	2.04	Y	0.76%	1.93	N
SUBC.NO	(0.08%)	(0.15)	N	(0.08%)	(0.12)	N
BAKKA.NO	(0.07%)	(0.14)	N	(0.06%)	(0.11)	N
All companies	0.11%	0.73	N	0.11%	0.79	N

Notes: 1) Small sample size for TOM.NO.

Figure 2: Development of Average Abnormal Return Around Report Issuance

This graph shows the Average Abnormal Return for the OBX Index constituents collectively, as measured by the y-axis in percentage, for fifteen days prior and three days after report issuance. The Average Abnormal Return has been computed using the same methodology for each date in the observed timeline, using the specifications illustrated in Figure 1. The grey line represents the results using the Fama French Three-Factor Model, whereas the black line represents the results using the Carhart Four-Factor Model. The red vertical line marks the event date (t=0), the day of report issuance used as the basis for this paper. Note that the y-axis has been scaled to visualise the differences between the two asset pricing models.



The results in Table 4 complement a visual presentation, observed in Figure 2, of the 15 days leading up to report issuance and the three subsequent days after issuance. Although this paper is focused on investigating the impact of sell-side reports on the day of issuance, we find that the reports create a significant average abnormal return on the first day following the issuance of a report for the collective group. On the first day after issuance (t=1), we find the average abnormal return to be 0.24% (t-value of 2.67) and 0.26% (t-value of 2.89) using the Fama French Three-Factor Model and Carhart Four-Factor Model, respectively.

The results for the average abnormal volume event study, as observed in Table 5, differs from that of the average abnormal return event study. First, by analysing the event study using the mean-adjusted model, 11 out of the 23 sample companies exhibit a statistically significant average abnormal volume on the day of issuance. This is also the case for the sample companies collectively, with an average abnormal volume of 23.94%[25] and a t-value of 8.66. It is worth noting that the average abnormal volume was positive for all statistically significant

[25] The Average Abnormal Volume has been transformed from the natural log of percentage of shares traded of the total number of shares outstanding to the percentage of anomaly (see section 5.3.3 for further explanation)

observations, with RECSI.NO having the highest significant AAV of 102.35% with the Mean-Adjusted Model.

The results for the event study using the Market Model are similar to those of the Mean-Adjusted Model, with 11 out of the 23 having statistically significant average abnormal volume on the days of issuance. The greatest average abnormal volume using the Market Model is observed for LSG.NO, having an average abnormal volume of 107.35%. There are some differences on an individual level for sample companies and the collective group. The main differences between the results for the Mean-Adjusted Model and the Market Model are that TEL.NO has a non-significant result for the Market Model, whereas it has a statistically significant result for the Mean-Adjusted Model, and TGS.NO has a statistically significant result using the Market Model, whereas it has a non-significant result when applying the Mean-Adjusted Model.

Table 5: Average Abnormal Volume Event Study Results

This table presents the average abnormal volume for each sample company. Each sample company is examined using the Mean-Adjusted Model and the Market Model to determine the average abnormal volume, then tested using a two-tailed cross-sectional t-test. The average abnormal volume is presented for each model, with the corresponding t-values and a column showing whether the average abnormal volume is significant at the 5% level for each sample company and if we can reject the null hypothesis, H_0 in favour of the alternative, H_A.

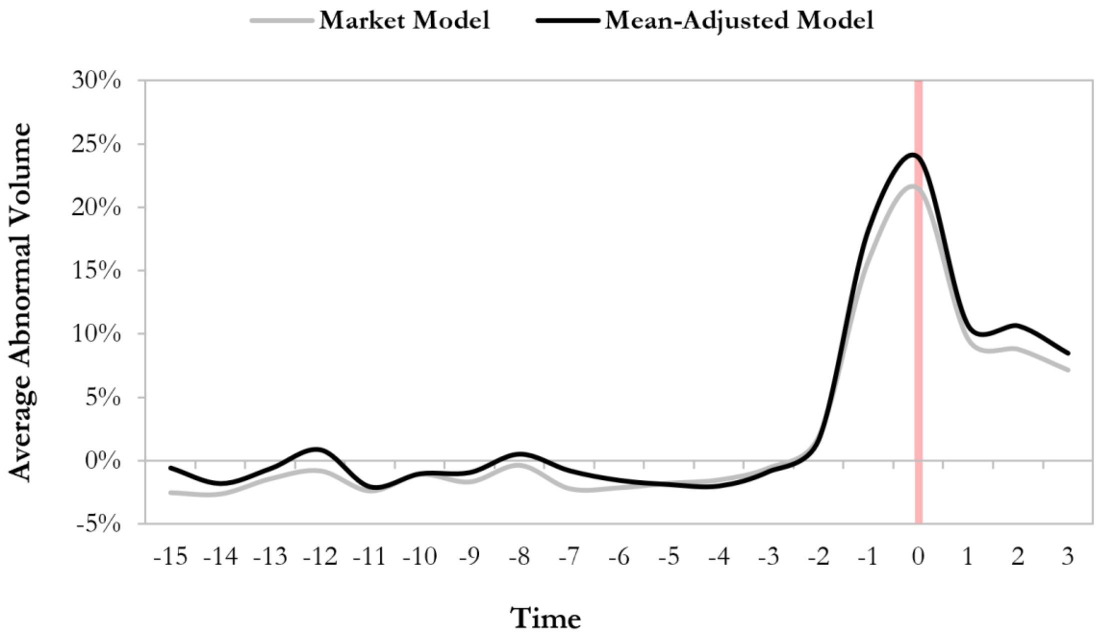
	Mean-Adjusted Model			**Market Model**		
Company ticker	Average Abnormal Volume	T-stat	Significant at 5% level (Y/N)	Average Abnormal Volume	T-stat	Significant at 5% level (Y/N)
AKSO.NO	11.08%	1.37	N	6.26%	0.72	N
ENTRA.NO	84.38%	1.99	Y	87.08%	2.21	Y
SCATC.NO	20.35%	0.96	N	20.43%	0.96	N
GJF.NO	22.75%	2.27	Y	21.19%	2.06	Y
AKRBP.NO	24.41%	2.48	Y	26.72%	3.18	Y
SALM.NO	7.92%	0.79	N	12.05%	1.23	N
AKER.NO	58.59%	2.61	Y	46.04%	3.03	Y
YAR.NO	35.92%	5.56	Y	32.53%	4.94	Y
RECSI.NO	102.35%	3.81	Y	34.41%	2.31	Y
EQNR.NO	12.07%	1.59	N	11.33%	1.60	N
NEL.NO	16.88%	0.43	N	1.06%	0.05	N
TEL.NO	18.87%	2.33	Y	15.76%	1.89	N
DNBH.NO	7.91%	1.00	N	8.32%	1.04	N
TOM.NO	(9.83%)	(0.38)	N	(4.63%)	(0.14)	N
NHY.NO	18.65%	2.36	Y	18.24%	2.33	Y
ORK.NO	12.90%	1.30	N	12.20%	1.11	N
LSG.NO	79.75%	3.41	Y	107.30%	5.74	Y
TGS.NO	22.72%	1.78	N	26.65%	2.12	Y
NOD.NO	59.72%	3.42	Y	55.12%	3.51	Y
MOWI.NO	12.35%	1.04	N	12.75%	1.04	N
STB.NO	16.12%	1.61	N	15.40%	1.64	N
SUBC.NO	(3.74%)	(0.43)	N	(5.16%)	(0.61)	N
BAKKA.NO	73.79%	3.09	Y	66.64%	2.89	Y
All companies	23.94%	8.66	Y	21.48%	8.37	Y

Notes: 1) Small sample size for TOM.NO.

As previously discussed, one model is not necessarily superior to the other. We speculate that the Market Model is more robust as the measured abnormal volume is lower than those found using the Mean-Adjusted Model. What remains consistent is the results for the collective group, with the group having a statistically significant average abnormal volume of 21.48% using the Market Model, which is relatively close to the AAV and t-value found using the Mean-Adjusted Model.

Figure 3: Development of Average Abnormal Volume Around Report Issuance

This graph shows the Average Abnormal Volume for the OBX Index constituents collectively, as measured by the y-axis in percentage, for 15 days prior and three days after issuance (red line). The Average Abnormal Volume has been computed using the same methodology for each date in the observed timeline, using the specifications presented in Figure 1. The grey line represents the Market Model results, whereas the black line represents the Mean-Adjusted Model results.



Here, as done with the results for the average abnormal returns, the results presented in Table 5 is complemented with Figure 3, showing the development of average abnormal volume for the OBX Index constituents collectively for the 15 days leading up to the report issuance and the three days following the issuance. As stated earlier, this paper aims to investigate the incremental changes on the day of issuance. However, we note statistically significant average abnormal volume on the day prior to report issuance and on one-, two- and three days after issuance, with the largest anomaly on the day of issuance (t=0). The average abnormal volumes are 14.7% and 16.78% (t-value of 5.49 and 5.93) on the day prior to, 9.14% and 10.12% (t-value of 4.19 and 4.35) the day after-, 8.44% and 8.54% (t-value of 4.04 and 3.73) two days after-, and 6.92% and 8.15% (t-value of 3.28 and 3.62) three days after report issuance for the Market Model and Mean-Adjusted Model respectively.

7.3 Individual-level results for sample companies

Whereas the two previous sections present the results concerning average abnormal returns and average abnormal volume for various report characteristics and the sample companies, this section presents summarised results from individual event studies for each sample company. Tables 6 and 7 are the results of looking at the various event dates for the sample companies and identifying single events that generate statistically significant anomalies at the 5% level. This part of the study intends to explain single reports' significance and effect on trading volume and stock returns. The results presented in this section do such on an individual company level using different methodologies than those applied in Section 7.1 and Section 7.2.

As described in Section 6, the methodology used in assessing abnormal return and abnormal volume on an event-by-event basis uses the standard t-test as seen in equations 6.15 and 6.17, respectively. In determining abnormal returns, we observe that 52 out of the 477 eligible sell-side reports generate a statistically significant abnormal return at the 5% level, using the Fama French Three-Factor Model. This number increases slightly to 60 out of 477 when using the Carhart Four-Factor Model, which adds momentum to the Fama French Three-Factor Model. In assessing abnormal volume, 53 out of 477 sell-side analyst reports generate abnormal volume on the day of issuance, using the Mean-Adjusted Model.

Similar to the assessment of abnormal returns, introducing additional factors increase the number of significant observations, where we found 63 out of 477 sell-side analyst reports generates abnormal volume using the more advanced Market Model. The results presented in Tables 6 and 7 show that approximately 11% of the sample recommendations generate statistically significant anomalies. However, these results are insufficient to draw a conclusion on an aggregate basis, which should be done based on Tables 2 through 5.

Table 6: Abnormal Return Event Study Results

This table presents summarised statistics for the individual event studies conducted with the significance testing of abnormal returns. Next to the tickers of the sample companies is the number of qualified observations, where a qualified observation does not overlap with other company-specific news. Further, the table presents the findings from the Fama French Three-Factor Model (FF3) and the Carhart Four-Factor Model (Carhart). Each model is accompanied by the number of significant observations (where the absolute t-value is greater than or equal to 1.96, meaning that we can reject the null hypothesis, H_0 in favour of the alternative, H_A), and the average measured AR (abnormal return), minimum AR and maximum AR for those observations deemed significant at the 5% level using a two-tailed t-test.

	Observations	**FF3**[1]				**Carhart**[1]			
Company ticker	Number of qualified observations	Number of significant observations	Average measured AR	Minimum AR	Maximum AR	Number of significant observations	Average measured AR	Minimum AR	Maximum AR
AKSO.NO	24	2	0.23%	(4.39%)	4.86%	2	0.37%	(4.12%)	4.86%
ENTRA.NO	10	2	8.23%	(2.28%)	18.74%	2	8.22%	(2.25%)	18.69%
SCATC.NO	23	4	(1.68%)	(6.38%)	11.09%	5	0.06%	(6.31%)	10.63%
GJF.NO	26	1	2.14%	2.14%	2.14%	1	2.14 %	2.14 %	2.14 %
AKRBP.NO	28	4	1.33%	(4.84%)	9.45%	3	2.63%	(4.83%)	8.60%
SALM.NO	22	2	1.14%	(4.08%)	6.36%	2	1.26%	(4.07%)	6.59%
AKER.NO	9	1	6.34%	6.34%	6.34%	2	4.96%	3.33%	6.60%
YAR.NO	37	6	(1.13%)	(4.04%)	4.40%	6	(1.03%)	(3.93%)	4.56%
RECSI.NO	15	3	16.05%	8.23%	27.90%	4	14.25%	8.08%	27.35%
EQNR.NO	34	3	(0.14%)	(4.99%)	7.16%	4	0.05%	(4.96%)	6.39%
NEL.NO	7	1	13.87%	13.87%	13.87%	1	14.09%	14.09%	14.09%
TEL.NO	20	1	(3.88%)	(3.88%)	(3.88%)	1	(3.89%)	(3.89%)	(3.89%)
DNBH.NO	31	5	0.85%	(3.15%)	4.11%	5	0.84%	(3.17%)	4.10%
TOM.NO	2	0	n.a[2]	n.a[2]	n.a[2]	0	n.a[2]	n.a[2]	n.a[2]
NHY.NO	33	4	0.92%	(4.89%)	8.11%	7	0.26%	(5.02%)	8.37%
ORK.NO	22	1	1.91%	1.91%	1.91%	1	1.88 %	1.88 %	1.88 %
LSG.NO	6	1	3.46%	3.46%	3.46%	1	3.49 %	3.49 %	3.49 %
TGS.NO	21	1	13.43%	13.43%	13.43%	2	9.32%	5.43%	13.20%
NOD.NO	27	4	(9.87%)	(23.44%)	(4.89%)	4	(9.78%)	(23.44%)	(4.63%)
MOWI.NO	22	2	(4.74%)	(5.88%)	(3.61%)	2	(4.86%)	(5.94%)	(3.78%)
STB.NO	28	2	6.46%	4.52%	8.41%	2	6.46%	4.48%	8.45%
SUBC.NO	21	2	(2.66%)	(9.25%)	3.93%	3	(3.84%)	(11.51%)	4.02%
BAKKA.NO	9	0	n.a[2]	n.a[2]	n.a[2]	0	n.a[2]	n.a[2]	n.a[2]
Total	477	52	n.a[2]	n.a[2]	n.a[2]	60	n.a[2]	n.a[2]	n.a[2]
Average	n.a[2]	n.a[2]	2.49%	(1.31%)	6.82%	n.a[2]	2.23%	(1.93%)	6.75%

Notes: 1) Average, minimum, and maximum AR values represent events statistically significant at the 5% level.
2) Not applicable.

Table 7: Abnormal Volume Event Study Results

This table presents summarised statistics for the individual event studies conducted concerning significance testing of the abnormal trading volume. Next to the tickers of the sample companies is the number of qualified observations, where a qualified observation does not overlap with other company-specific news. Further, the table presents the findings using the Mead-Adjusted Model and the Market Model. Each model is accompanied by the number of significant observations (where the absolute t-value is greater than or equal to 1.96, meaning that we can reject the null hypothesis, H_0 in favour of the alternative, H_A), and the average measured AV (abnormal volume), minimum AV and maximum AV for those observations deemed significant at the 5% level using a two-tailed t-test. The average, minimum and maximum AR is the percentage of the abnormal trading volume.

	Observations	**Mean-Adjusted Model[1]**				**Market Model[1]**			
Company ticker	Number of qualified observations	Number of significant observations	Average measured AV	Minimum AV	Maximum AV	Number of significant observations	Average measured AV	Minimum AV	Maximum AV
AKSO.NO	24	1	171.94%	(33.69%)	171.94%	1	182.08%	(52.10%)	182.08%
ENTRA.NO	10	2	998.59%	621.25%	1,375.93%	2	871.68%	561.14%	1,182.22%
SCATC.NO	23	5	212.79%	(83.81%)	510.90%	5	219.13%	(83.80%)	512.32%
GJF.NO	26	4	148.87 %	123.48 %	195.01 %	6	142.66 %	91.12 %	180.35 %
AKRBP.NO	28	2	272.17%	182.72%	361.63%	2	197.77%	144.18%	251.35%
SALM.NO	22	2	26.48%	(61.18%)	114.14%	1	(60.98%)	(60.98%)	(60.98%)
AKER.NO	9	2	268.00%	238.11%	297.90%	0	n.a[2]	n.a[2]	n.a[2]
YAR.NO	37	5	142.72%	91.28%	218.99%	7	120.69%	82.54%	182.58%
RECSI.NO	15	2	415.94%	327.44%	504.43%	0	n.a[2]	n.a[2]	n.a[2]
EQNR.NO	34	4	173.11%	117.38%	215.04%	5	133.05%	103.33%	192.04%
NEL.NO	7	1	459.48%	459.48%	459.48%	1	(65.43%)	(65.43%)	(65.43%)
TEL.NO	20	1	151.12%	151.12%	151.12%	2	110.66%	84.78%	136.53%
DNBH.NO	31	1	131.57%	131.57%	131.57%	3	62.20%	(54.87%)	152.68%
TOM.NO	2	0	n.a[2]	n.a[2]	n.a[2]	0	n.a[2]	n.a[2]	n.a[2]
NHY.NO	33	3	148.49%	120.15%	168.12%	7	67.47%	(53.77%)	160.92%
ORK.NO	22	1	181.82 %	181.82 %	181.82 %	4	62.37 %	-58.75 %	233.93 %
LSG.NO	6	1	180.84 %	180.84 %	180.84 %	2	202.34 %	209.83 %	194.86 %
TGS.NO	21	3	231.12%	163.17%	340.34%	3	205.05%	102.97%	284.21%
NOD.NO	27	6	394.15%	224.50%	971.59%	4	387.16%	198.08%	758.72%
MOWI.NO	22	2	198.77%	189.58%	207.97%	4	74.59%	(51.58%)	237.48%
STB.NO	28	2	206.78%	146.60%	266.96%	1	241.15%	241.15%	241.15%
SUBC.NO	21	1	238.08%	238.08%	238.08%	1	206.76%	206.76%	206.76%
BAKKA.NO	9	2	282.92%	155.72%	410.13%	2	261.39%	152.81%	369.97%
Total	477	53	n.a[2]	n.a[2]	n.a[2]	63	n.a[2]	n.a[2]	n.a[2]
Average	n.a[2]	n.a[2]	256.17%	175.71%	348.81%	n.a[2]	181.09%	80.83%	251.53%

Notes: 1) Average, minimum, and maximum AV values represent events statistically significant at the 5% level.
2) Not applicable.

8. Discussion

This chapter discusses the results presented in Section 7 and the overall study. In Section 8.1, we outline and interpret the possible implications of our findings. Then, in Section 8.2, we discuss some of the limitations to the analyses conducted and opportunities for further research on the subject.

8.1 Implications of findings

Several findings from the study are worth highlighting, both in terms of returns and trading volume. It is clear from the results presented in Section 7 that the sell-side reports appear to have a greater influence on generating abnormal volume than abnormal returns on the day of issuance. The vast majority of observations do not generate a statistically significant abnormal return other than for a few individual stocks. We are not to speculate why these companies experienced abnormal returns; a suggestion is made in Section 7. However, we observe statistically significant abnormal returns (average abnormal return) for reports that are either *upgrades* or *downgrades*. Additionally, we find that the collective group of sample companies experienced average abnormal returns the day following report issuance.

Given that the sample companies as a collective group do not experience any significant average abnormal returns on the day of report issuance, the statistical significance of *upgrades* and *downgrades* leads us to think that the insignificant results for the collective group as presented in Table 4 are affected by a large number of *No change* recommendations. This report characteristic did not exhibit any anomalies. In other words, a sell-side report generates abnormal returns when a change in the recommendation is made, and reiteration of recommendations do not create any statistically significant abnormal return. These findings are consistent with those of Goksøyr & Grønn (2019), who found that the largest anomalies were generated when a report deviated from consensus or there was a change in the recommendation. Furthermore, as noted in Section 7.1, these results are relatively consistent with those of Jegadeesh & Kim (2006); we find upgraded recommendations on the Oslo Stock Exchange to have a similar effect on stock returns as upgraded recommendations do in the US. This is in contrast to the findings of Su et al. (2018), who found that upgraded recommendations did not generate abnormalities for securities on the London Stock Exchange and the Alternative Investment Market.

The lack of abnormal returns *on the day of report issuance* may indicate that the managers of OBX Index constituents are better at managing market and analysts' expectations ahead of accounting releases (and thus also quarterly preview recommendations) than managers of firms in countries where abnormal return patterns are prevalent. Another possible explanation can be found in the way we constructed our dataset. Because we obtained and entered the recommendation data manually, we were able to exclude reports issued in conjunction with company reports and other idiosyncratic news releases from the sample. As Ryan & Taffler (2002) found that firm accounting releases was the source of information with the highest probability of generating abnormal returns for a company's stock, the failure to exclude such recommendations from the sample may result in Type 1 errors.

The hypothesis formulation and the event window construction are of utter importance for the results obtained. This study is focused on the incremental changes on the day of report issuance; however, as described in Section 7.2, we find statistically significant abnormal returns on the day following the report issuance. Although we are critical to the treatment of overlapping events in Goksøyr & Grønn (2019), which investigates the same stock index as this paper, further studies need to be conducted for a clear comparison of results and significance. It is worth noting that Goksøyr & Grønn's significant findings are found using a longer event window.

In terms of average abnormal volume, we find statistically significant average abnormal volume for the collective group as observed in Table 5. Particularly interesting is that *Updates* and *Quarterly Reviews* generate statistically significant average abnormal volume, as seen in Table 3. Updates might be released after a firm-specific news release, such as the announcement of an acquisition or production troubles; however, we have cleaned the dataset for overlaps between these events and report issuances. The Updates and Quarterly Reviews are, based on our observations, frequently featured in the Norwegian financial press. We speculate that the significance of the Quarterly Reviews stems from analysts being able to convey the information concerning the larger equity story of the company, especially for non-professional investors. This way of thinking would align with Ryan & Taffler's (2002) observations regarding analysts being a vital distributor of information. We find no statistically significant abnormal return on days where a Quarterly Preview is issued. These reports are issued in the days or weeks leading up to accounting figures release, and the results could imply that there is no significant change in neither stock returns nor trading volume when presenting a limited report that does not necessarily provide anything new to the market. In other words, there is no value add or increased investor recognition from Quarterly Previews, and only qualitative reports such as *Updates* or *Quarterly Reports* have such an effect. As for the anomalies we find, we do not know the true drivers behind them and whether institutional investors or retail investors are driving the spikes. This question would, speculatively, be more straightforward to answer in a market such as the American due to the considerable publicity that sell-side reports get in the Norwegian financial press combined with significantly fewer listed entities in the Norwegian market. Based on the reports in the sample and as seen in Tables 4 and 5, sell-side reports generate abnormal volume, yet no abnormal return. This leads us to think that the report's recommendation is not as important as the report being issued itself. It could be possible that any report exhibiting the characteristics found in this study can generate investor recognition to the extent that *smart money* offsets the *feedback traders*[26] and others.

It is well documented in the extant literature that sell-side analysts are more inclined to issue buy recommendations than sell recommendations (e.g., Previts et al., 1994; Mikhail et al., 2004; Jegadeesh et al., 2004; Chen & Matsumoto, 2006). This is also clear from our sample. Out of 1319 recommendations analysed, 53.6% were buy recommendations, 37.1% hold, and 9.3% were sell recommendations. A factor that might help explain the recommendation pattern is the market sentiment. During the period examined in this study, the Oslo Stock Exchange Benchmark Index (OSEBX) appreciated by approximately 72%. Given the overall market's returns, one might think it natural for analysts to issue fewer sell recommendations than buy recommendations, but one should think analysts are more inclined to issue sell recommendations during bear markets by the same intuition. This, however, does not always seem to be the case.

Barber et al. (2007) found that analysts at investment banks were very reluctant to downgrade their recommendations during the bear market of the early 2000s. Similarly, CNBC (Fahey, 2017) investigated data dating back 20 years on the composition of buy, hold, and sell recommendations of S&P500 companies and found that the share of active sell/underweight recommendations only made up approximately 6% of total recommendations on average. In fact, according to the market data provided by FactSet, this percentage figure did not once surpass 10%, even during the dot-com crisis of the early 2000s and the Great Recession of 07-08. In their study on sell recommendations and analyst credibility, Hilary & Shon (2006) argue

[26] See section 2.1.2

that this phenomenon is consistent with investors suffering from an optimistic behavioural bias. Optimistic investors tend to assign lower credibility to analysts' recommendations contrary to their beliefs. Analysts are thus subject to collective market pressure to hype stocks and will hence be more likely to issue a buy recommendation than a sell recommendation in fear of being side-lined. They also find that market reactions to earnings forecasts are weaker when adjusting for the number of prior sell recommendations issued for other firms he or she follows (especially in periods where positive market sentiment persists over time), hinting at the implication that sell recommendations generate negative credibility associations towards the analyst who issues them. We find no such tendency for the Norwegian brokerage analysed in our sample.

8.2 Limitations of study and opportunities for future research

This paper is, to our knowledge, the first to analyse the effects of sell-side reports on both stock returns and the trading volume for companies listed on the Oslo Stock Exchange and the first to analyse such effects from reports issued by a Norwegian operating investment bank. A significant amount of time has been spent manually collecting data, reflected in the uniqueness and robustness of the data sample utilised and the results produced.

There are a few limitations to bear in mind. The use of reports from only one investment bank provides results solely for this investment bank and cannot be generalised for all firms providing sell-side research on Norwegian listed firms. Jegadeesh & Kim (2006) argue that the analysts with the most value-add are behind anomalies stemming from report issuances. We believe that the sell-side research provider used in this data sample would fall under such category for the Norwegian stock market, having a more significant impact on stock behaviour than a less recognisable provider with lower value-add analysts. These results are only applicable to said provider for OBX Index constituents. Results could differ if all Oslo Stock Exchange-listed entities were analysed, and we are careful in generalising the findings to the entire platform.

These two limitations are primarily driven by the time constraint of manually collecting all reports combined with the lack of access to reports from multiple Norwegian investment banks. A possible solution to this is to have access to a database such as the I/B/E/S database; however, this will not guarantee valid results as there might be overlap between firm-specific news and report issuances that are difficult to identify when downloading a dataset from a provider such as I/B/E/S.

There are endless opportunities for further research on the topics covered in this paper, but there are a few ideas that we want to pass on to our readers. Based on this thesis, we have used a framework for exploring the Norwegian stock market that is transferable to larger datasets and suitable for introducing additional variables. One of such variables that could be interesting to explore further is the volatility measure, as seen in Panchenko (2007), and how the issuance of sell-side reports affects volatility and its implications for option pricing. Furthermore, we recommend comparing how the market reacts to recommendations from foreign sell-side analysts versus domestic analysts by comparing the effects of the recommendations of foreign and domestic analysts on the same sample of stocks. Such research would complement this thesis and the work of Jegadeesh & Kim (2006), who found that US analysts generate the most value for investors.

9. Conclusion

This thesis investigates the relationship between sell-side equity research reports, stock returns, and the trading volume for the most liquid stocks traded on the Oslo Stock Exchange (the OBX Index), using reports issued by a Norwegian operating investment bank.

We find that sell-side reports generate abnormal volume on the day of report issuance for the collective group of sample companies through the event study methodology, with insignificant results for a few individual companies. Using two different expected volume models, we find the abnormal volume on the day of report issuance to be 21.48% and 23.94%. Additionally, we find statistically significant average abnormal volume on the day before- and the days after report issuance. Of the reports analysed, we find that *buy* recommendations lead to the Market Model's largest anomalies, with an increase in trading volume of 24.22%. From the Mean-Adjusted Model (24.22%), we find that the largest abnormal volume was driven by *hold* recommendations (24.51%). Furthermore, we find that any report generates abnormal volume regardless of whether the recommendation has changed. Stocks that received an upgraded rating experienced an increase in trading volume of 47.34% and 49.01%, using the two models, whereas stocks that received a downgraded rating experienced an increase of 39.83% and 35.13%. The average abnormal volume from unchanged recommendations is lower than those of reports with changed recommendations, at 17.88% and 20.48%.

We find no statistically significant abnormal returns on the day of report issuance for the collective group; however, we find statistically significant abnormal returns on the first day after following report issuance. As for the day of issuance, we find that stocks receiving a rating revised upwards experience an abnormal return of 2.04% and 2.08% through two expected return models. Similarly, we find that revised downwards stocks experience an abnormal return of -0.85% and -0.87%. Furthermore, stocks that receive a target price reduction between 0% and 10% experienced an abnormal return of -0.68% using either model.

Further research on the topic can examine whether these results apply to a more significant number of Oslo Stock Exchange-listed entities as well as a broader universe of sell-side research providers.

References

Barber, B., Lehavy, R., McNichols, M., & Trueman, B. (2001). Can investors profit from the prophets? Security analyst recommendations and stock returns. *The Journal of Finance, 56*(2), 531–563. https://doi.org/10.1111/0022-1082.00336

Barber, B. M., Lehavy, R., & Trueman, B. (2007). Comparing the stock recommendation performance of investment banks and independent research firms. *Journal of Financial Economics*, *85*(2), 490–517. https://doi.org/10.1016/j.jfineco.2005.09.004

Brown, S. J., & Warner, J. B. (1980). Measuring security price performance. *Journal of Financial Economics*, *8*(3), 205–258. https://doi.org/10.1016/0304-405x(80)90002-1

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns. *Journal of Financial Economics, 14*(1), 3–31. https://doi.org/10.1016/0304-405x(85)90042-x

Børsprosjektet. NHH. (2021). Retrieved October 20, 2021, from https://www.nhh.no/forskning/borsprosjektet/.

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997). *The econometrics of financial markets*. Princeton, N.J: Princeton University Press.

Campbell, C. J., & Wasley, C. E. (1996). Measuring abnormal daily trading volume for samples of NYSE/ASE and NASDAQ Securities using parametric and nonparametric test statistics. *Review of Quantitative Finance and Accounting*, 6(3), 309–326. https://doi.org/10.1007/bf00245187 978-0-444-50898-0

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1), 57–82. https://doi.org/10.1111/j.1540-6261.1997.tb03808.x

Chen, S., & Matsumoto, D. A. (2006). Favorable versus unfavorable recommendations: The impact on analyst access to management-provided information. *Journal of Accounting Research*, *44*(4), 657–689. https://doi.org/10.1111/j.1475-679x.2006.00217.x

Clark, P. K. (1973). A subordinated stochastic process model with finite variance for speculative prices. *Econometrica*, *41*(1), 135–155. https://doi.org/10.2307/1913889

Cready, W. M., & Ramanan, R. (1991). The power of tests employing log-transformed volume in detecting abnormal trading. *Journal of Accounting and Economics*, 14(2), 203–214. https://doi.org/10.1016/0165-4101(91)90005-9

de Long, J. B., Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *The Journal of Finance*, *45*(2), 379. https://doi.org/10.2307/2328662

Eckbo, B. E. (2009). Handbook of Corporate Finance: Empirical Corporate Finance (1st ed., Vol. 1). Elsevier North-Holland.

Euronext. (2021, June 30). *OBX*. Retrieved September 19, 2021, from https://live.euronext.com/sites/default/files/documentation/index-factsheets/OBX_20210630.pdf

Euronext. (2020, November 17). *Oslo Børs Index Weightings files - availability in PRE-PRODUCTION*. Euronext Live. Retrieved November 3, 2021, from https://live.euronext.com/en/market-data-news/view/15328.

Fahey, M. (2017, February 6). Why wall street analysts almost never put 'sell' ratings on the stocks they cover. CNBC. Retrieved November 8, 2021, from https://www.cnbc.com/2017/01/26/sell-ratings-by-wall-street-analysts-almost-never-happen.html.

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The Journal of Finance,* 25(2), 383-417. http://dx.doi.org/10.2307/2325486

Fama, E. F. (1976). Efficient capital markets: reply. *The Journal of Finance,* 31(1), 143-145.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and Bonds. *Journal of Financial Economics,* 33(1), 3–56. https://doi.org/10.1016/0304-405x(93)90023-5

French, K. R. (2021). Kenneth R. French - Data library. Retrieved October 20, 2021, from http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Gibson, G. (1889). The Stock Markets of London, Paris and New York, G.P. Putnam's Sons, New York.

Goksøyr, O.-M., & Grønn, L. A. (2019). Stoler markedet på analytikerne? : en empirisk studie av analytikeranbefalingers påvirkning på aksjemarkedet. https://doi.org/https://openaccess.nhh.no/nhh-xmlui/bitstream/handle/11250/2609803/masterthesis.PDF?sequence=1&isAllowed=y

Green, T. C. (2006). The value of client access to analyst recommendations. *Journal of Financial and Quantitative Analysis, 41*(1), 1–24. https://doi.org/10.1017/s0022109000002404

Grossman, S.J., Stiglitz, J.E. (1980). On the Impossibility of Informationally Efficient Markets. *The American Economic Review*, 70(3), pp. 393-408.

Groysberg, B., Healy, P. M., & Maber, D. A. (2011). What drives Sell-Side Analyst compensation at High-Status investment banks? *Journal of Accounting Research, 49*(4), 969–1000. https://doi.org/10.1111/j.1475-679x.2011.00417.x

Hilary, G. & Shon, J. (2006) "Sell Recommendations, Market Sentiment, and Analyst Credibility", Working Paper. Available from: https://www8.gsb.columbia.edu/faculty-research/sites/faculty-research/files/accounting/HILARY.pdf

Huang, Y., & Wei, S. X. (2011). Advertising intensity, investor recognition, and implied cost of capital. *Review of Quantitative Finance and Accounting*, *38*(3), 275–298. https://doi.org/10.1007/s11156-011-0228-1

Hudson, R. S., & Gregoriou, A. (2015). Calculating and comparing security returns is harder than you think: A comparison between logarithmic and simple returns. *International Review of Financial Analysis*, *38,* 151–162. https://doi.org/10.1016/j.irfa.2014.10.008

Jegadeesh, N., Kim, J., Krische, S. D., & Lee, C. M. (2004). Analysing the analysts: When do recommendations add value? *The Journal of Finance*, *59*(3), 1083–1124. https://doi.org/10.1111/j.1540-6261.2004.00657.x

Jegadeesh, N., & Kim, W. (2006). Value of analyst recommendations: International evidence. *Journal of Financial Markets*, *9*(3), 274–309. https://doi.org/10.1016/j.finmar.2006.05.001

Jung, B., K. Sun, and S. Yang. 2012. Do financial analysts add value by facilitating more effective monitoring of firms' activities? *Journal of Accounting, Auditing and Finance,* 27(1), 61-99.

Li, K. K., & You, H. (2015). What is the value of sell-side analysts? Evidence from coverage initiation. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2636643

Lidén, E. R. (2007). Swedish stock recommendations: Information content or price pressure? *Multinational Finance Journal,* 11(3/4), 253–285. https://doi.org/10.17578/11-3/4-4

Lin, H. W., & McNichols, M. F. (1998). Underwriting relationships, analysts' earnings forecasts and investment recommendations. *Journal of Accounting and Economics*, *25*(1), 101–127. https://doi.org/10.1016/s0165-4101(98)00016-0

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risk Investments in Stock Portfolios and Capital Budgets, *Review of Economic Statictics 47.*

Lo, A. W. (2004). The adaptive markets hypothesis. *The Journal of Portfolio Management*, *30*(5), 15–29. https://doi.org/10.3905/jpm.2004.442611

MacKinlay, C. A. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature 35* (1), 13–39.

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*(3), 483–510. https://doi.org/10.1111/j.1540-6261.1987.tb04565.x

Michaely, R., & Womack, K. L. (1999). Conflict of interest and the credibility of underwriter analyst recommendations. *Review of Financial Studies*, *12*(4), 653–686. https://doi.org/10.1093/rfs/12.4.653

Mikhail, M. B., Walther, B. R., & Willis, R. H. (2004). Do security analysts exhibit persistent differences in stock picking ability? *Journal of Financial Economics*, *74*(1), 67–91. https://doi.org/10.1016/j.jfineco.2003.11.001

Miller, E. M. (1977). Risk, uncertainty, and divergence of opinion. *The Journal of Finance*, *32*(4), 1151–1168. https://doi.org/10.1111/j.1540-6261.1977.tb03317.x

Mossin, J. (1966). Equilibrium in a capital asset market. *Econometrica: Journal of the Econometric Society*, 768-783.

Panchenko, V. (2007). Impact of analysts' recommendations on stock performance. *The European Journal of Finance*, *13*(2), 165–179. https://doi.org/10.1080/13518470500459782

Perold, A. (2004). The Capital Asset Pricing Model. *The Journal of Economic Perspectives*, 18(3), 3-24. Retrieved October 18, 2020, from http://www.jstor.org/stable/3216804.

Previts, G. J., Bricker, R. J., Robinson, T. R., & Young, S. J. (1994, June). A content analysis of sell-side financial analyst company reports. *Accounting Horizons*, 8(2), pp. 55-70.

Richardson, S., Sloan, R., & You, H. (2012). What makes stock prices move? Fundamentals vs. investor recognition. *Financial Analysts Journal*, *68*(2), 30–50. https://doi.org/10.2469/faj.v68.n2.2

Ryan, P., & Taffler, R. J. (2002). What firm-specific news releases drive economically significant stock returns and trading volumes? *Journal of Business Finance & Accounting*, *31*(1-2), 49–82. https://doi.org/10.2139/ssrn.314880

Sewell, M. V. (2012). The efficient market hypothesis: Empirical evidence. *International Journal of Statistics and Probability*, *1*(2). https://doi.org/10.5539/ijsp.v1n2p164

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3), 425-442.

Shiller, R. J. (1981). Do Stock Prices Move Too Much to be Justified by Subsequent Changes in Dividends? *The American Economic Review*, *71*(3), 421–436. http://www.jstor.org/stable/1802789

Shiller, R. J. (2003). From efficient markets theory to behavioral finance. *Journal of Economic Perspectives*, *17*(1), 83–104. https://doi.org/10.1257/089533003321164967

Simon, H. A. (1956). Rational choice and the structure of the environment. *Psychological Review*, *63*(2), 129–138. https://doi.org/10.1037/h0042769

Souček, M., & Wasserek, T. (2014). Impact of analyst recommendations on stock returns: Evidence from the German stock market. *Discussion Papers 358, European University Viadrina Frankfurt (Oder), Department of Business Administration and Economics*.

Stickel, S. E. (1995). The anatomy of the performance of buy and sell recommendations. *Financial Analysts Journal*, *51*(5), 25–39. https://doi.org/10.2469/faj.v51.n5.1933

Su, C., Zhang, H., Bangassa, K., & Joseph, N. L. (2018). On the investment value of sell-side analyst recommendation revisions in the UK. *Review of Quantitative Finance and Accounting*, *53*(1), 257–293. https://doi.org/10.1007/s11156-018-0749-y

Sun, B., Sanchez Carrete, L., & Tavares, R. (2017). Impact of sell-side reccomendation reports on stock returns. *REVISTA EVIDENCIAÇÃO CONTÁBIL & FINANÇAS*, *5*(3), 22–36. https://doi.org/10.18405/recfin201703022

Appendices

Appendix A: Overview of Sample Companies

Table A.1: Sample Companies

This table presents the companies researched in the study. The table shows the stock ticker (Ticker), corresponding company name (Company Name), industry classification (Industry) according to the research reports, listing year (Year Listed), the date of the first recommendation included in the sample (First Sample Recommendation), and the market capitalisation figures at the end of 2020 (Mkt Cap.).

Ticker	Company Name	Industry	Year Listed	First Sample Recommendation	Mkt. Cap (NOKm)
AKER.NO	Aker (Class A)	Investment Companies	2004	21.12.2017	40,108
AKRBP.NO	Aker BP	E&P	2006	28.01.2016	75,420
AKSO.NO	Aker Solutions	Oil Services	2014	08.02.2016	8,093
BAKKA.NO	Bakkafrost	Seafood	2010	05.01.2016	35,813
DNB.NO	DNB Bank	Banks	1992	13.01.2016	237,150
ENTRA.NO	Entra	Real Estate	2014	07.06.2016	34,467
EQNR.NO	Equinor	E&P	2001	28.01.2016	462,636
GJF.NO	Gjensidige Forsikring	Insurance	2010	05.01.2016	89,500
LSG.NO	Lerøy Seafood	Seafood	2002	23.02.2016	34,568
MOWI.NO	Mowi	Seafood	1997	21.01.2016	97,196
NEL.NO	NEL	Power and Renewable	2004	02.12.2019	40,908
NHY.NO	Norsk Hydro	Metals & Mining	1909	12.01.2016	80,691
NOD.NO	Nordic Semiconductor	Hardware & Equipment	1996	20.01.2016	26,634
ORK.NO	Orkla	Diversified Consumer	1929	11.02.2016	84,084
RECSI.NO	Rec Silicon	Renewables & Clean Tech	2006	04.02.2016	5,952
SALM.NO	SalMar	Seafood	2007	19.02.2016	57,466
SCATC.NO	Scatec	Power and Renewable	2014	15.01.2016	53,901
STB.NO	Storebrand	Insurance	1993	04.01.2016	28,792
SUBC.NO	Subsea 7	Oil Services	2005	29.02.2016	25,500
TEL.NO	Telenor	Telecom	2000	20.01.2016	190,264
TGS.NO	TGS	Seismic	1998	11.01.2016	14,761
TOM.NO	TOMRA Systems	Industrials	1985	01.10.2020	62,160
YAR.NO	Yara International	Agriculture	2004	07.01.2016	83,003

Appendix B: Security Returns

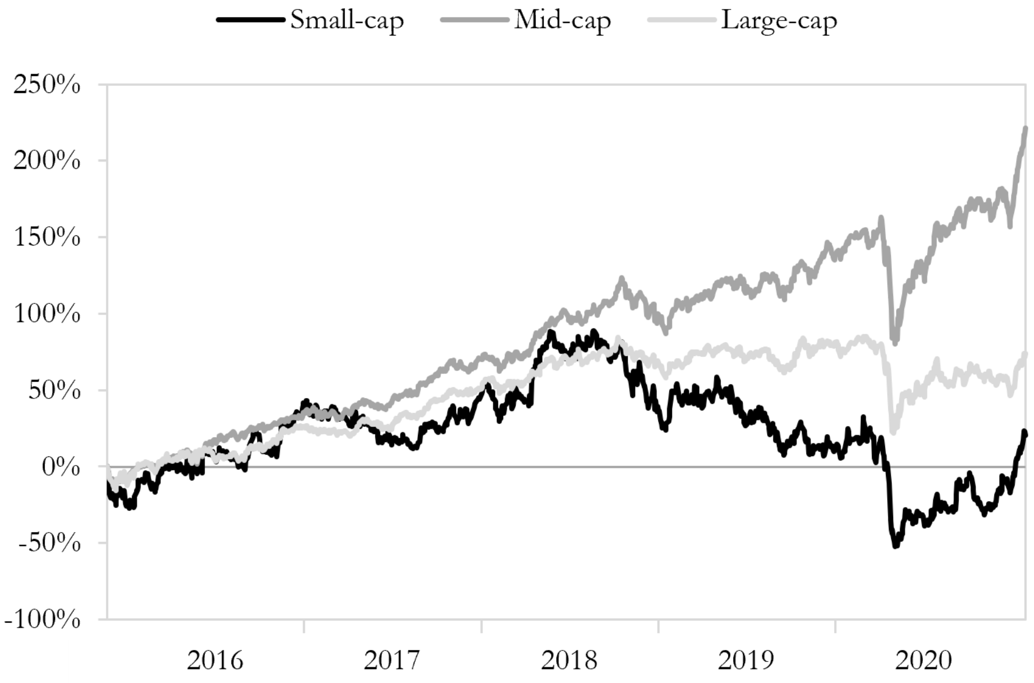
Table B.1: Security Returns for Sample Companies

This table presents the annual stock returns for the companies investigated in this study. Annual returns are displayed for each company ticker (Ticker) for the years in the sample (2016 to 2020). Each ticker is accompanied by the simple average annual return (Average annual return) and the annualised return (Annualised return). The two last rows display the simple average annual return for the entire sample, in addition to the value-weighted return based on the market capitalisation figures found in Table A.1.

	Returns						
Ticker	**2016**	**2017**	**2018**	**2019**	**2020**	**Average annual return**	**Annualised return**
AKER.NO	127.50%	28.60%	26.60%	(1.60%)	19.90%	40.20%	34.00%
AKRBP.NO	234.00%	40.10%	6.80%	21.30%	(20.00%)	56.50%	37.00%
AKSO.NO	69.90%	0.10%	3.50%	(59.50%)	6.00%	4.00%	(5.00%)
BAKKA.NO	35.10%	5.80%	25.20%	58.10%	(7.00%)	23.40%	21.00%
DNB.NO	35.60%	17.00%	(5.10%)	8.90%	2.50%	11.80%	11.00%
ENTRA.NO	25.00%	40.00%	(0.80%)	29.70%	26.10%	24.00%	23.00%
EQNR.NO	46.80%	15.00%	3.30%	(5.80%)	(11.20%)	9.60%	8.00%
GJF.NO	3.00%	13.80%	(12.10%)	38.40%	2.10%	9.00%	8.00%
LSG.NO	43.10%	(11.50%)	66.90%	(11.60%)	1.50%	17.70%	14.00%
MOWI.NO	131.20%	(10.20%)	37.50%	20.90%	(16.80%)	32.50%	23.00%
NEL.NO	(43.20%)	60.90%	65.20%	71.50%	249.70%	80.80%	55.00%
NHY.NO	54.20%	35.40%	(34.10%)	(20.20%)	26.70%	12.40%	7.00%
NOD.NO	(7.10%)	31.90%	(36.40%)	91.70%	142.10%	44.50%	29.00%
ORK.NO	14.60%	6.70%	(16.10%)	27.60%	(3.60%)	5.80%	5.00%
RECSI.NO	(6.70%)	1.30%	(54.40%)	(41.50%)	382.60%	56.30%	4.00%
SALM.NO	48.40%	(6.70%)	94.60%	6.00%	8.00%	30.10%	25.00%
SCATC.NO	7.50%	29.20%	57.40%	65.20%	130.80%	58.00%	53.00%
STB.NO	50.10%	42.60%	(7.30%)	11.30%	(5.00%)	18.30%	16.00%
SUBC.NO	121.00%	16.70%	(27.70%)	12.80%	(19.20%)	20.70%	11.00%
TEL.NO	(6.10%)	39.00%	(9.30%)	(2.70%)	(10.70%)	2.00%	1.00%
TGS.NO	67.40%	2.50%	19.00%	5.50%	(48.60%)	9.20%	2.00%
TOM.NO	2.70%	47.00%	58.80%	30.90%	50.20%	37.90%	36.00%
YAR.NO	0.50%	9.40%	(7.40%)	(2.30%)	10.70%	2.20%	2.00%
Average return	45.90%	19.80%	11.00%	15.40%	39.90%	-	-
Value-weighted return	43.60%	20.00%	7.50%	10.90%	10.80%	-	-

Figure B.1: Value-Weighted Cumulative Returns for Small-, Mid- and Large-cap

This figure presents the value-weighted cumulative performance of the sample companies based on their market capitalisation (Small-cap, Mid-cap, and Large-cap). The returns presented are based on daily stock price data, indexed on 3 January 2016, and value-weighted according to market capitalisation as of the end of 2020.



Appendix C: Frequency Distributions

Figure C.1: Frequency Distribution of Security Returns

This figure presents the frequency distribution of daily security returns for the sample companies (grey bars) in addition to the Gaussian distribution (black line) of returns using the mean and standard deviation of returns. The frequency of returns is measured along the y-axis, whereas the x-axis displays the returns (bins).

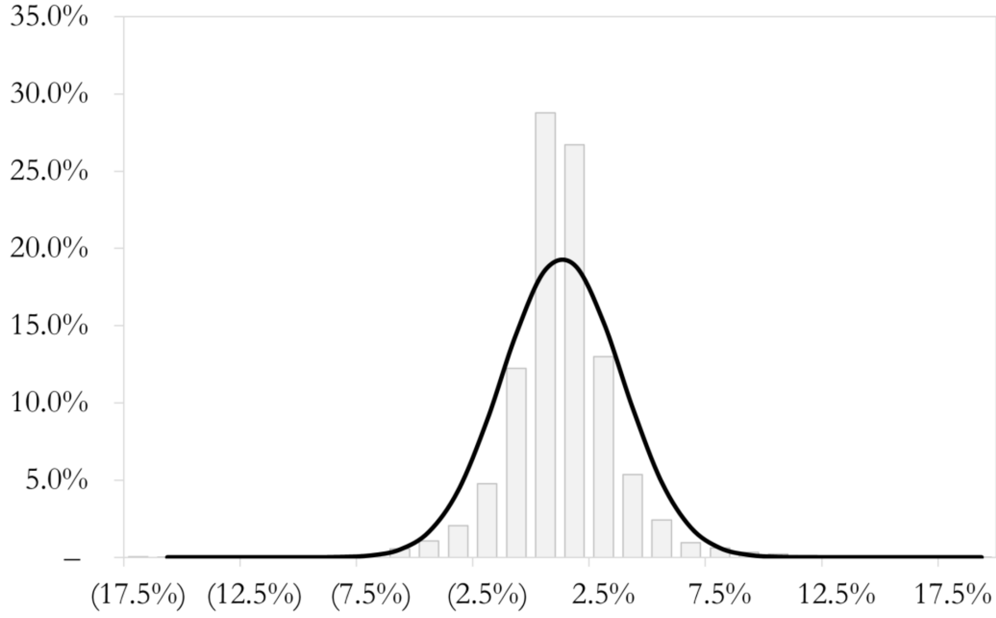


Figure C.2: Frequency Distribution of Natural-Log of Trading Volume

This figure presents the frequency distribution of trading volume post natural-log transformation for the sample companies (grey bars) in addition to the Gaussian distribution (black line) of natural-log trading volume using the mean and standard deviation of transformed trading volumes. The frequency of natural-log trading volume is measured along the y-axis, whereas the x-axis displays the natural-log (bins).