Norwegian School of Economics
Bergen, Spring 2023

Trading on Inside Track

An Event Study of Market Reactions to Legal Insider Trading on the Oslo Stock Exchange

Marius Birkeland and Kevin Maosheng Li

Supervisor: Tommy Stamland

Master thesis, Economics and Business Administration

Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgments

This thesis concludes our Master of Science in Economics and Business Administration with a major in Financial Economics at the Norwegian School of Economics. Our interest in financial markets' theoretical and practical aspects has evolved throughout our academic journey. Therefore, we wanted to choose a topic with profound theoretical concepts while being practically feasible.

Studying reported insider trades has been a challenging yet fascinating process for us. Our research has enriched our understanding of insider trading, market efficiency, event methodology, and data analysis. We have acquired significant knowledge in these areas, which has been instrumental in shaping our perspective on the financial markets.

We want to express our utmost gratitude to our supervisor, Tommy Stamland, for his helpful guidance and support throughout the process of writing this thesis. His constructive feedback and challenging questions have significantly contributed to the final product. Moreover, we are grateful to our families and friends for their unconditional support and encouragement.

Norwegian School of Economics

Bergen, June 2023

Marius Birkeland

Kevin Maosheng Li

Abstract

This master thesis investigates the market reactions to legal insider trading on the Oslo Stock Exchange using the methodology outlined by MacKinlay (1997). The analysis is based on a sample of 2419 insider trades publicly disclosed between 01.01.2017 and 31.12.2022.

The results of the event study suggest that insider purchases generate significantly abnormal returns, yielding 1.14 percent for the full sample in the event window [0, 1]. We observe a pattern indicating that larger transactions yield higher abnormal returns than smaller transactions. However, we do not observe a similar pattern for insider sales. Furthermore, the market reacts more strongly to purchases made by insiders higher up in the company hierarchy, such as chief officers and chairs.

The market reactions were stronger for insider purchases within industrial companies and in R&D-intense companies, specifically in the health care and information technology industry. Conversely, insider sales within companies related to information technology, industrials, and financial services gave significantly negative abnormal returns. Finally, for our cross-sectional regression analysis, larger companies and companies with a high share of insider ownership had a negative effect on the abnormal return. On the opposite side, insider purchases in companies with higher volatility and liquidity positively affect abnormal returns.

Keywords: *Legal insider trading, information asymmetry, efficient markets, Oslo Stock Exchange*

Contents

List of Figures

List of Tables

1 Introduction

1.1 Motivation and Purpose

All insiders in a firm possess valuable information that can be utilized for their benefit. This is a well-known fact in the market, making insider trading a crucial determinant of price movements for a stock. If insider trading is deemed legal and insiders do not act on illegal information, there should be no market reactions. Even though information on insider trading is publicly available and reported to the authorities, the market still reacts strongly to it. Therefore, further investigation of the market reaction's significance would be interesting.

"Inside track" can be referred to as having an advantageous competitive position (Oxford University Press, n.d.). Due to insiders' privileged position regarding trading shares in their own company, there is an asymmetric information distribution between insiders and outsiders, leading to market reactions to insider trading. Our research focuses on the investigation of asymmetric information. Furthermore, we aim to explore the presence of strong-form market efficiency, which implies that all public and non-public information is already incorporated into the current stock price (Fama, 1970). In such a market, abnormal returns are not possible. However, previous research indicates that positive abnormal returns are achievable after insider trading (Jaffe, 1974; Seyhun, 1986).

1.2 Research Question

Prior research has extensively examined the cumulative abnormal return (CAR) as a measure of the impact of insider trading on share prices. Similarly, our study has adopted MacKinlay's (1997) methodology for calculating CAR. Various factors have been considered in previous studies while investigating CAR, such as the insider's position and the transaction size's magnitude, to determine the effect of insider trading on stock prices. In addition to these factors, we are investigating the impact of insider trading on the stock prices concerning the company's industry and specific event and firm characteristics. Based on this, we aim to investigate the following main question:

> *What impact does transaction size, insider position, industry, and specific event and firm characteristics have on the magnitude and significance of the market's response to legal insider trading?*

1.3 Structure of the Thesis

The subsequent sections of the thesis are structured as follows: In Chapter 2, we will provide an overview of relevant theoretical frameworks to our research, including market efficiency and information asymmetry. We will also review previous research related to insider trading and our thesis. Subsequently, we will present and explain our selection of hypotheses in Chapter 3. Chapters 4 and 5 will provide details on the data and the methodology used in the analysis, and the analysis itself will be presented in Chapter 6. A robustness testing chapter will follow the analysis. Finally, the limitations of this thesis, a conclusion and suggestions for further research will be provided.

2 Literature Review

2.1 Insider Trading

Insider trading is a phenomenon that has attracted significant attention and scrutiny from both regulators and market participants. It refers to the practice of trading stocks or other securities by individuals who possess material or non-public information about the company or security (Ganti, 2022). The Financial Supervisory Authority of Norway further states that inside information is information that is precise, suitable to influence the price of the financial instruments if the information is made public and directly or indirectly affects several financial instruments (Finanstilsynet, 2022a). Insiders are members of the company's administrative, management, or control body and have regular access to inside information or authority to make decisions at the management level (Finanstilsynet, 2022b). Individuals subject to these requirements include CEOs, top executives, members of the board of directors, and large shareholders, among others.

The Norwegian Securities Trading Act regulates securities trading in Norway. The act aims to ensure that securities trading in Norway is conducted fairly and transparently, and that insider trading does not unfairly benefit insiders at the expense of uninformed market participants (Verdipapirhandelloven, 2007). Under the act, insiders are required to report their trades to The Financial Supervisory Authority of Norway according to the requirements imposed by The Norwegian Securities Trading Act. The reporting must be done promptly, but no later than before the opening of the following trading day. Our thesis is focused on legal insider trading, and from now on, we will refer to legal insider trading as insider trading.

Seyhun (1998) provides three motives for insider trading. According to Seyhun, profit is the most eminent motivation for insiders trading shares in their company. The reason is that insiders possess knowledge that outsiders do not, which enables them to more accurately evaluate whether the firm's market value is correct. Hence, insiders are incentivized to take advantage of this information asymmetry if the market price does not align with their understanding of the company's intrinsic value.

Secondly, Seyhun (1998) argues that insiders often have a liquidity motive for selling shares, as they may need to rebalance their portfolios or obtain personal liquidity. This is particularly true for insiders who hold significant wealth in their company's shares. When such insiders sell a large portion of their shares, it can be perceived negatively and affect the company's prospects. Seyhun (1998) describes the third and final motivation as the manipulation motive, wherein insiders seek to manipulate the market through their trades. For instance, insiders may decide to sell their shares to send a negative signal to the market and cause the price to drop. Insiders are then allowed to purchase more shares at a later point in time for a lower price. Conversely, insiders may buy shares despite having information that suggests they should not. This behavior may be due to the positive signaling effect insiders want to convey to the market by purchasing shares.

A common motivation for insider purchases is to exert greater control over the company's operations, including strategic direction and management decisions. Beams (2002, p.56) concluded that an individual's intention to participate in insider trading is significantly influenced by factors such as the potential for gain, the level of certainty, cynicism, guilt, social stigma, and alignment with the law.

2.2 Market Efficiency

The market efficiency hypothesis is predicated on research conducted by Kendall and Hill (1953), which suggested that stock market movements approximate a random walk. The hypothesis asserts that stock prices reflect all available information concerning the underlying firm (Fama, 1970). Therefore, any known information is unlikely to help predict future stock price movements. Instead, any new information is promptly incorporated into the stock price, ensuring that it always accurately reflects the true underlying value of the share (Brealey et al., 2017).

Stock prices are believed to contain varying degrees of information about past prices and market conditions. Fama (1970) proposed a classification system for market efficiency, which comprises three degrees of efficiency: weak, semi-strong, and strong efficiency. The classification is based on the degree to which stock prices in the market are based on information.

In a weakly efficient market, the stock price reflects all available information regarding past prices. The information regarding past prices is considered public. Therefore, knowledge of this information does not confer a competitive advantage. Consequently, it is not possible to achieve abnormal returns merely by studying past prices, rendering technical analysis valueless. Most empirical evidence suggests that weak-form market efficiency prevails, supporting the random walk model (Fama, 1995). Access to public and private information regarding firms, such as financial statements and strategic analysis of growth opportunities, is required to surpass a weak-form efficient market.

A semi-strong efficient market integrates all publicly available information and future expectations, including information about past prices, into the current price. The prices will have already been adjusted for all publicly available information, rendering fundamental analysis useless. The only possible way to achieve abnormal returns in such a market is by accessing insider information from the companies.

In a strong-form efficient market, public and non-public information regarding companies is fully reflected in the companies' stock prices. Consequently, any information, regardless of its origin or nature, will be insufficient to generate abnormal returns.

If abnormal returns are observed after an insider trade, it could potentially imply a violation of the strong-form market efficiency hypothesis, suggesting that not all information is fully incorporated into the share price. Conversely, Manne (1966) concluded in his study that insider trading effectively conveys information to the stock market and maintains a theoretically correct share price. Finnerty (1976) argues insider trading may increase market efficiency by helping insiders make informed decisions, investing in firms with good prospects, and reducing information asymmetry. It can also incentivize companies to improve their information flow to the market and ensure that prices reflect underlying fundamentals.

2.3 Information Asymmetry

The term "information asymmetry" refers to a scenario in which one party involved in a transaction possesses an inadequate level of knowledge regarding the other party. This lack of information makes it difficult to make informed decisions during the course of the transaction (Mishkin, 2003).

Akerlof's (1970) seminal contribution to the asymmetric information theory is among the earliest and most influential in this field. His work demonstrated the adverse effects of information asymmetry on market outcomes, highlighting the adverse selection or “lemon problem”. Adverse selection is a phenomenon that arises when one party in a transaction possesses superior information, also known as hidden information, before entering into an agreement (Laffont & Martimort, 2009). Furthermore, the concept of the lemon problem argues that an elevated degree of information asymmetry leads to a greater probability of mispricing on the stock market. Therefore, we anticipate that firms with a greater degree of information asymmetry are more likely to exhibit more significant market reactions.

Information asymmetry among investors represents a prominent manifestation of market inefficiency (Ryu et al., 2022). This phenomenon is crucial in facilitating insider trading as it allows insiders to profit at the expense of uninformed investors (Chae, 2005; Del Brio et al., 2002). Insiders possess superior knowledge and access to non-public information (Jaffe, 1974), such as financial performance, prospects, and sensitive details about a company. This information advantage enables insiders to anticipate company share price changes before public disclosure, resulting in trading activity that can benefit from such knowledge. Hence, the information asymmetry between insiders and the public can serve as a facilitator for insider trading.

2.3.1 Intangible Assets and R&D

Intangible assets refer to assets that are not physical (Kenton, 2022a). These assets are more difficult to value for outsiders than tangible ones (Levine et al., 2017). Huddart and Ke (2010) further suggest that information asymmetry is closely related to the type of assets a firm possesses. Barth and Kasznik (1999) argue that a higher proportion of intangible assets in the firm's total assets indicates greater variations in intrinsic value. Therefore, we believe that the greater the proportion of intangible assets, the higher the level of information asymmetry. Firth et al. (2011) conducted a study and found that insider trading activity is more intense when the proportion of intangible assets in the total assets is higher. They conclude that insiders tend to trade more shares to signal the firm's value when there is a high level of information asymmetry, which is more likely to occur when the proportion of intangible assets is high.

Further discussion will be dedicated to research and development (R&D), which often represents a significant portion of intangible assets. The advantages of utilizing R&D inputs to achieve a competitive advantage are substantial and associated with information asymmetries (Coff & Lee, 2002). Thus, investors often perceive managerial trading as a critical indicator of a firm's resource quality.

Coff and Lee (2002) analyzed the stock price reactions of more than 134,000 insider trading events. They discovered that insider purchases produce significantly greater positive stock price reactions for firms with high R&D intensity. Furthermore, their research findings suggest that R&D intensity has a positive association with cumulative abnormal returns for insider purchases, indicated by a change of 0.044 percentage points, and a negative association for insider sales, indicated by a change of -0.013 percentage points.[1]

Aboody and Lev (2000) assert that R&D activities create a significant information asymmetry for two primary reasons. Firstly, assets resulting from R&D investments are often more unique than tangible assets, leading to greater difficulty in valuing them accurately. Secondly, the markets for trading intellectual property that emerges from R&D expenditures are relatively less organized than those for physical and financial assets, resulting in a lack of transparency in obtaining pertinent information to assess the value of such assets. In the same paper by Aboody and Lev (2000), they examined the gains accrued by insiders in relation to R&D activities as a source of asymmetric information. Their study concluded that firms with greater R&D intensity exhibited significantly higher abnormal returns with a monthly mean raw return of 5.49 percent as opposed to 4.47 percent for non-R&D firms.

To the best of our knowledge, no research has been conducted on insider trading among high-intensity R&D firms on the Norwegian stock market. Consequently, it would be intriguing to investigate whether our findings will be consistent with prior international studies.

2.3.2 Position within the Company

Insiders holding higher positions within a company are often associated with greater access to information, as highlighted by Seyhun (1986) and Fidrmuc et al. (2006). Consequently, we anticipate that insider trades executed by individuals in higher positions yield higher abnormal returns, as the market perceives such transactions as more valuable. For instance, an insider trade by a CEO is likely to be attributed more value by outsiders compared to a purchase made by an insider in the HR department.

Previous studies investigating the relationship between position in the company and cumulative abnormal returns have utilized different criteria for defining positions. For example, Seyhun (1986) focused exclusively on managers, board members, chairs, and major shareholders within a company. In our analysis, we will be using somewhat different positions than Seyhun, which will be elaborated on in Chapter 3.

[1] Coff and Lee (2002) use R&D-intensity as an independent variable in their analysis, which is calculated as the ratio of R&D expenditures to total sales.

3 Hypotheses

The literature review has provided an understanding of the existing research on insider trading and related theory. A common characteristic observed across the studies we have reviewed is that insider trading causes market reactions. Therefore, it is reasonable to assert that market activities contain information about the direction of a security's price and offer valuable insights into its future stock trajectory. Hence, we have formulated the following hypothesis:

HYPOTHESIS I: *Insider trades on the Oslo Stock Exchange cause short-term abnormal returns.*

If insiders engage in transactions involving significant transaction values, it may suggest they have a higher confidence level in their actions. This confidence may stem from their access to insider knowledge regarding the company's financial health, prospects, or other pertinent non-public information. Larger transactions may have a greater impact on the market than smaller ones due to the significant volume of traded shares and the heightened attention that such transactions garner from market participants. Thereby, we have the following hypothesis:

HYPOTHESIS II: *Market reactions*[2] *to insider trades on the Oslo Stock Exchange are stronger for larger transaction sizes than for smaller transaction sizes*.

We suggest that a higher position in the company hierarchy implies greater access to information and, thereby, a higher potential for additional returns. Investigating whether market reactions to insider trading differ based on the trader's position within the company would be an interesting avenue to explore on the Oslo Stock Exchange, as it has not been explored before, to the best of our knowledge. We have classified the positions hierarchically as follows: CEOs, CFOs, other C-suites, chairs, board members, stakeholders, and others. Positions such as executive vice presidents, vice presidents, directors, and other insiders of lower position were combined under *others* to provide clearer categorization. The *other C-suits* category includes all chief officers[3] except the CEOs and CFOs, as we wanted to look at these two positions separately, given their possibly significantly greater access to key information. Thereby, we hypothesize the following:

[2] Market reactions refer to abnormal returns.
[3] This includes the following chief officers: CIO, CSO, CLO, CTO, CHRO, COO, CMO, and CCO.

HYPOTHESIS III: *Market reactions to insider trading on the Oslo Stock Exchange are stronger for insiders with a higher position in the company than those with a lower position.*

Furthermore, we aim to investigate if insider trading impacts CAR differently across various industries. Particularly, we aim to explore whether CAR is more affected by insider trading in R&D-intensive industries than in other industries. As health care and information technology industries are known to have a higher concentration of R&D-intensive firms (National Science Board, 2020), we propose that the effect of insider trading on abnormal returns will be more pronounced in these industries. Hence, we have formulated the following hypothesis:

HYPOTHESIS IV: *Market reactions to insider trades on the Oslo Stock Exchange are stronger for R&D-intense firms than non-R&D-intense firms.*

In addition, we want to examine whether specific event and firm characteristics affect the outcome of abnormal returns in the case of insider trading. These characteristics are related to the company size, the relative size of the transaction, the profitability, the risk and liquidity, the company's solvency, and whether there is a high portion of insiders owning shares.[4] Based on this, we have formulated the following hypothesis:

HYPOTHESIS V: *The magnitude and direction of the market reactions associated with insider trading are influenced by certain event and firm characteristics.*

[4] The specific characteristics used in this analysis is described in Chapter 5.2.1.

4 Data

This chapter provides an overview of the data sources used in our study and the objectives employed in the data cleansing process. Initially, we shall describe the approach used to extract insider trading and stock data. Finally, we will present a comprehensive overview of the descriptive statistics of our dataset. The data covered in this chapter are used to calculate the cumulative average abnormal returns for the event study. The data utilized in our cross-sectional regression analysis is covered in Chapter 5.2.1.

4.1 Data Selection: Insider Trades

This thesis investigates the market reactions associated with insider trading on the Oslo Stock Exchange from 01.01.2017 to 31.12.2022. The decision to include data from the COVID-19 pandemic period in this study was motivated by the fact that, as far as we know, no other master´s thesis examining insider trading has included this particular period. We are excluding transactions according to three conditions, as listed in the table below:

Table 1: Conditions for Excluding Insider Trades

Starting point: Total number of announcements on NewsWeb under the category ”MANDATORY NOTIFICATION OF TRADE PRIMARY INSIDERS” from 01.01.2017 to 31.12.2022.

Condition 1: Excluding all non-discretionary trades, such as trades related to total return swap agreements, options, warrants, payment schemes, and stocks on discount.

Condition 2: Excluding trades below NOK 100,000.

Condition 3: Excluding insider trades on stocks with less than 130 days of trading data prior to the announcement date.

Condition	Excluded	Remaining
Starting point	-	8,927
1	4,745	4,182
2	964	3,218
3	799	2,419

To fulfill the first condition, we have limited the data selection process to only include purchases and sales made by primary insiders or companies under their control. Share distributions as part of corporate bonus programs and the allocation or exercising of options are not included. The same applies to other derivatives, such as total return swaps agreements, warrants, and futures. This limitation aligns with the aim of examining discretionary trades. According to Jaffe (1974), the utilization of options is frequently influenced by institutional factors rather than insider possession of privileged information. Coff and Lee (2002) assert that transactions involving the exercise of options and shares obtained from compensation plans should be omitted from the dataset as they tend to provide minimal new insights into the company's overall value.

The second condition implies that we have solely included transactions with a value surpassing NOK 100,000 in our dataset, given that low-value insider transactions tend to produce a less robust signal (Lakonishok & Lee, 2001). We have converted all transactions in foreign currencies to NOK by using exchange rates provided by Norges Bank (n.d.) at the time of the transaction.

According to condition three, we exclude insider transactions where there is insufficient historical data to calculate the abnormal return. As described later in Chapter 5.4, our study employs the market model using an estimation period of 10 to 130 days prior to the announcement date. For instance, if an insider trade occurs on the same day a stock is listed, no prior trading data exists, and the market model cannot be used to calculate abnormal returns. Consequently, such an insider transaction is excluded from the analysis. In contrast, if there is enough trading history available for a given stock, in our case 130 days, the abnormal return can be computed, and the corresponding insider trade is included in the analysis.

The insider trades have been obtained directly from NewsWeb, a dataset made available by the Oslo Stock Exchange. The notifications contained within NewsWeb are in the form of textual strings, requiring manual extraction of the necessary information. The information of interest for extraction includes the ticker name, company name, insider's position within the company, an indication of purchase or sale, date, volume, price, and currency of the transaction.[5]

Our dataset consists of 2,419 observations of insider trading, of which 2,033 pertain to insider purchases and 386 to insider sales. There are several reasons why insider purchases are observed more frequently than insider sales. Firstly, insiders tend to avoid selling shares unless

[5] An illustrative example of an insider trade notification as displayed on NewsWeb is presented in Appendix A.

necessary, as it may send negative signals to the market and affect their stock holdings. Secondly, insiders may be unable to sell shares due to lock-up regulations, which further contributes to the higher frequency of insider purchases.

To further investigate the large difference between the number of insider purchases and sales, we ran a simple linear regression between the net purchase ratio and the average age of all companies.[6] We argue that if Oslo Stock Exchange has many young companies, there will be an overweight of insider purchases compared to sales on the stock exchange for mainly two reasons. Firstly, young companies may be more likely to be in a growth phase, motivating insiders to participate in the company's development early on. Secondly, in the case of young and potentially newly listed companies, a dual effect can arise due to a probable initial low ownership of shares by insiders and the introduction of an opportunity for insiders to acquire shares. This combination can create an imbalance, leading to a potential disparity between the number of insider purchases and insider sales. However, in Table 9 in Appendix A, we found no significant relationship between the two variables, indicating that the large difference between the number of insider purchases compared to insider sales cannot be explained by the company age.

4.2 Data Selection: Stocks and Benchmark

To obtain information concerning the companies listed on the Oslo Stock Exchange, we used the Bloomberg Terminal. Bloomberg collects this data from the Oslo Stock Exchange directly. The extracted stock data consists of the adjusted closing price for all the stocks in our dataset. The stock data was extracted for the period 01.01.2017 to 31.12.2022. The adjusted closing prices account for corporate actions, such as dividends and stock splits during the specified period. Daily observations were employed in this study, as they are deemed preferable when the event date is clearly identified, as noted by MacKinlay (1997).

In addition, MacKinlay (1997) argues that when conducting an event study, it is necessary to employ a broad-based stock index as a benchmark to calculate normal returns. Our analysis investigates insider transactions for all stocks on the Oslo Stock Exchange. Accordingly, the Oslo Stock Exchange All-share Index (OSEAX) was selected for this purpose. The OSEAX is

[6] The average age of the companies is measured as the average number of years from the insider trade to the listing date for each company. The net purchase ratio is measured as purchases less sales, divided by the total number of insider trades within the company.

a value-weighted stock market index that tracks the performance of all listed securities on the Oslo Stock Exchange, adjusted for dividend payments and other corporate actions (Medleva, 2019). The prices for the OSEAX during the specified period were likewise obtained from the Bloomberg database.

4.3 Descriptive Statistics

Table 2: Descriptive Statistics

The table provides descriptive statistics of insider trades and related characteristics on the Oslo Stock Exchange reported between 01.01.2017 and 31.12.2022, with a minimum transaction size of NOK 100,000. Each data point in the dataset represents a specific insider trade and its corresponding characteristics. The table presents the median, mean, standard deviation, minimum, and maximum values of the following variables: Transaction Size (in mNOK), Company Size (in mNOK), Turnover (percent), Intangible Assets (percent of market capitalization), Altman's Z-score, Transaction Size ratio (percent of mCap), Number of Insider Owners, Insider Ownership ratio (percent), 30-Day Volatility, Price-to-Book, Return on Equity (percent), Revenue Growth (percent), Enterprise Multiple, and Price-to-Earnings.

Panel A [Purchases]

Characteristic	Median	Mean	SD	Min	Max
Transaction Size	0.28	4.19	42.23	0.1	1935
Company Size	3140	15221	45281	84	458228
Turnover	0.14	0.25	0.35	0.002	5.1
Intangible Assets	0.63	6.3	14	0	95
Altman's Z-score	2	3.8	5.4	0	36
Transaction Size ratio	0.021	0.14	0.44	0.0002	4.2
Number of Insider Owners[7]	6	7.6	5.9	0	53
Insider Ownership ratio[7]	0.41	2.2	4.5	0	31
30-Day Volatility	37	43	24	10	143
Price-to-Book	1.5	2.2	2.1	0.1	13
Return on Equity	4.5	4	22	-89	95
Revenue Growth	8.2	14	43	-91	243
Enterprise Multiple	11	13	8.8	1	59
Price-to-Earnings	19	30	30	0.2	193

[7] As explained later in Chapter 5.2.1, insider ownership data is extracted before the insider transaction, so the value can be zero if there are no owners prior to the transaction.

Panel B [Sales]

Characteristic	Median	Mean	SD	Min	Max
Transaction Size	1.3	15.35	71.97	0.1	1066
Company Size	5004	38382	126153	60	740249
Turnover	0.15	0.33	0.63	0.003	5.1
Intangible Assets	1.4	4.7	7.8	0	47
Altman's Z-score	2.5	3.3	3.4	0	19
Transaction Size ratio	0.045	0.5	1.4	0.0001	8.9
Number of Insider Owners	8	8.5	5.7	0	31
Insider Ownership ratio	0.86	3.3	8	0	65
30-Day Volatility	36	50	46	9.9	299
Price-to-Book	2.2	4.5	5.2	0.1	22
Return on Equity	9.4	9	28	-63	80
Revenue Growth	12	16	36	-65	146
Enterprise Multiple	10	12	9.9	0.044	57
Price-to-Earnings	17	26	30	0.67	173

Table 2 displays descriptive statistics for insider purchases and sales for all characteristics used in our cross-sectional regression analysis, further covered in Chapter 5.2.1. In addition, the table displays the transaction size.

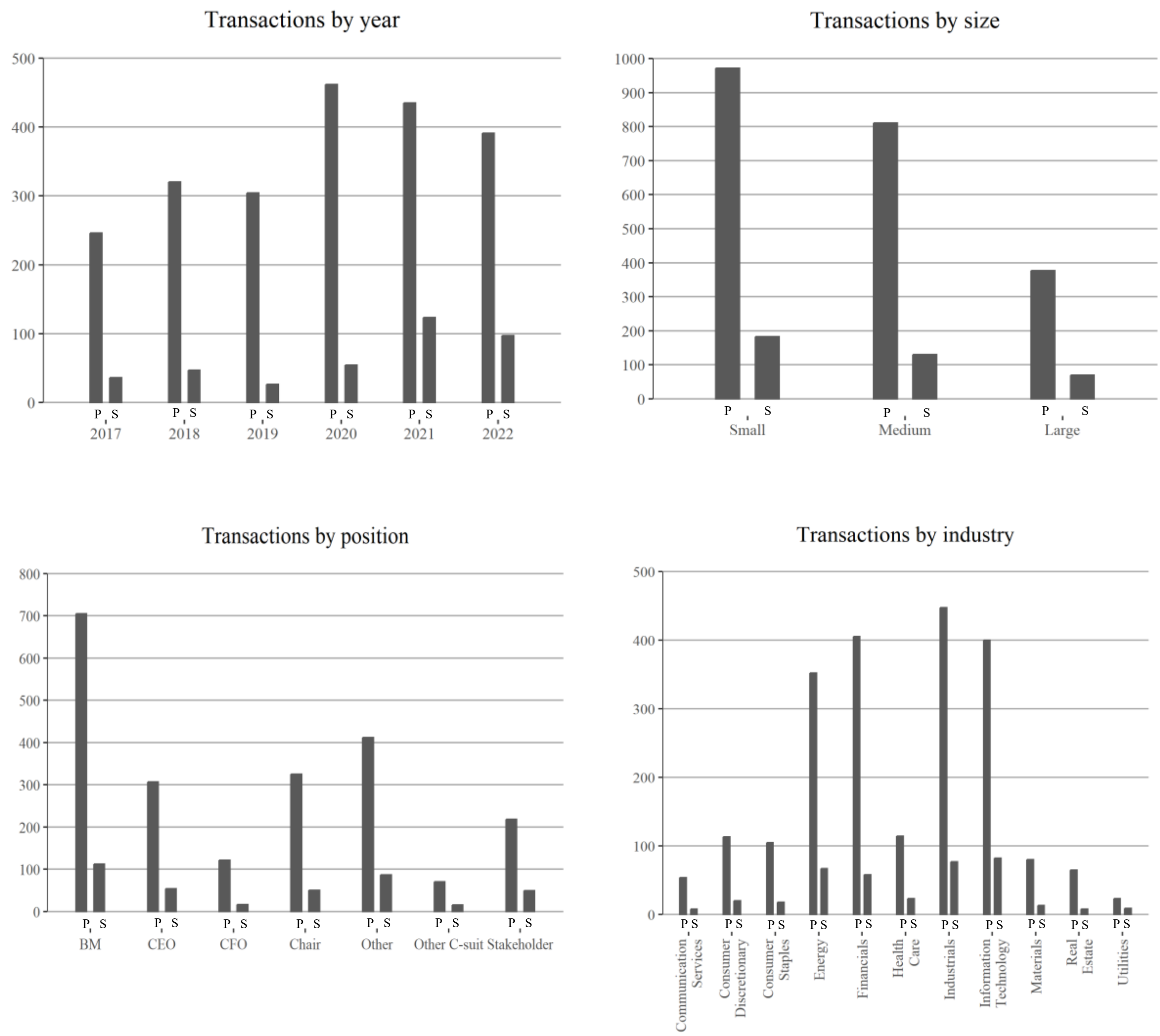
The mean *transaction size* is higher for insider sales than for insider purchases. One plausible explanation for this observation is that some insiders may offload large volumes of stocks upon resigning from their positions. This explanation is supported by the fact that the mean is almost four times higher for insider sales than for purchases. We also observe higher median and standard deviation values for *company size*. A possible explanation is that larger companies have a larger number of insiders and a higher staff turnover than smaller companies. Hence, as people leave the company, they will most likely sell large portions of their shares, if not the entire equity stake. In addition, insider trading activity might be more common in larger companies, making it more acceptable for insiders to also sell shares without worrying about the company's stock price.

In Panel A in Table 2, it is evident that the maximum of *intangible assets* amounts to 95% of market capitalization. This is attributed to the substantial portion of intangible assets the company Akastor AS holds relative to their market capitalization. Moreover, the mean *price-to-earnings* ratio for purchases and sales seems somewhat higher than expected. According to Nordea, the price-to-earnings ratio on the Oslo Stock Exchange was 15.4, based on expected earnings for 2023 (Tronstad, 2022). The difference may be because OSEAX is calculated using the total net income of all companies divided by the total market capitalization. However, in the descriptive statistics for our dataset, we utilize only the mean of all observations. This implies that a company with many insider trades (high number of observations) and a high corresponding price-to-earnings ratio will have a greater weightage than a company with few trades (low number of observations) and a low corresponding price-to-earnings ratio.

4.4 Distribution of Insider Trades

Figure 1: Distribution of Insider Trades

This figure shows the registered insider trades in our dataset for the Oslo Stock Exchange from 01.01.2017 to 31.12.2022. The data has been categorized for purchases (P) and sales (S) based on year, transaction size, position in the company, and industry.



The transaction size has been further categorized into low, medium, and large groups. Transactions with a value ranging from NOK 100,000 to NOK 500,000 fall within the low-size group, while transactions ranging from NOK 500,000 to NOK 5,000,000 are classified as medium-sized transactions. Finally, transactions exceeding NOK 5,000,000 are designated as large transactions. Industries are classified based on the Global Industry Classification Standard (GICS) scheme for industry categorization (MSCI, n.d.). The categorization of positions was discussed in Chapter 3.

The figure above shows that most insider trades occurred between 2020 and 2022, with the largest increase between 2019 and 2020. The portion of sales compared to purchases is the highest for 2021. Further, most transactions fall within the *small* category, followed by the *medium* category, while the least number of observations are noted within the *large* category.

The category *BM* (*board member*) made the most insider purchases, followed by *others* and *chair*. As for insider sales, there is no definitive difference between the groups, but *CFO*, *board member*, and *other* are the ones who carry out the most insider sales. Most transactions are concentrated in the four industry groups *Industrials, Information Technology, Financials*, and *Energy*. The remaining industries show a comparable number of transactions, with the lowest amounts found within *Utilities* and *Communication Services*.

5 Methodology

An event study is a common approach in financial research to assess the impact of a specific event on stock returns. Using the event study methodology, our goal is to determine the influence of insider trading on the stock prices of companies listed on the Oslo Stock Exchange. We aim to examine whether the market reacts to insider transactions by identifying abnormal returns.

The following sections will discuss the event study methodology, outline the technique for measuring abnormal returns, and describe the cross-sectional regression employed to analyze the impact of insider trades on the Oslo Stock Exchange.

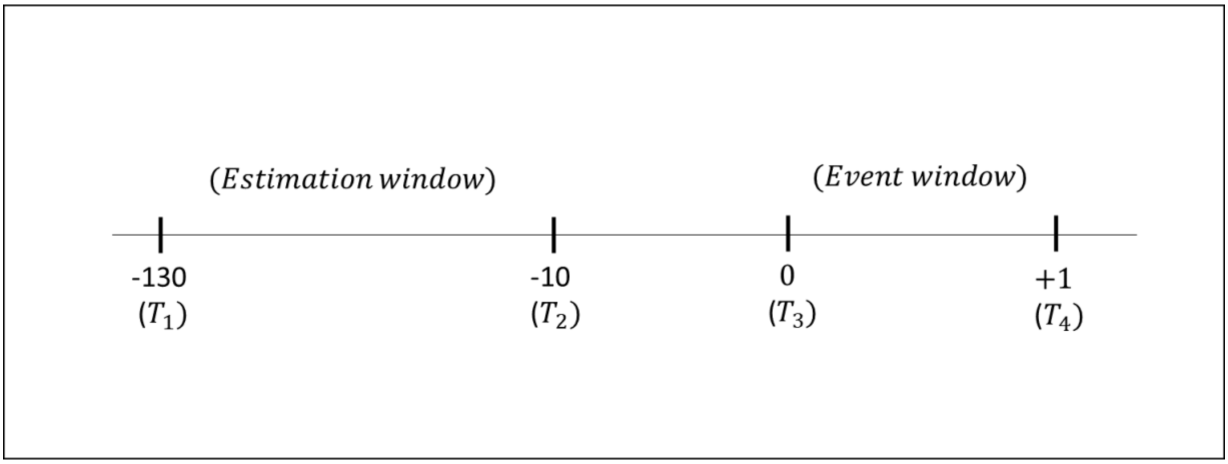
5.1 The Event Study Methodology

The analytical approach adopted in this thesis is primarily based on the framework proposed by MacKinlay (1997). According to MacKinlay, an event study can be conducted using the following systematic approach:

1. Clearly define the event of interest.
2. Define the event window.
3. Establish criteria for selecting companies to be included in the study.
4. Select an appropriate model for estimating normal returns, along with the duration of the estimation window.
5. Calculate abnormal returns and perform statistical tests to assess the significance of the event's impact.

It should be noted that the third step has already undergone revision in Chapter 4.1, and thus, the subsequent sections will concentrate on the remaining steps.

Figure 2: Illustration of the Event Study



where:

$T_1 - T_2$ is the estimation window of 120 days

$T_2 - T_3$ is the gap between the end of the estimation window and the start of the event window of ten days

$T_3 - T_4$ is the event window of two days

5.1.1 Defining Events

The primary goal of this thesis is to examine the stock market's response to insider trading announcements. The event of interest in this investigation are the insider trades reported on NewsWeb.

5.1.2 Defining Event Window

The event window can be defined as a temporal period that surrounds a specific event. By including additional days beyond the actual event date, the potential impact of events announced after the closure of the stock exchange can be measured (MacKinlay, 1997). Furthermore, McWilliams and Siegel (1997) argue that an extended event window can reveal information leakage prior to insider trading and capture delayed market reactions. Given that daily expected returns are nearly zero, a short window that includes a few days after the event is advantageous in capturing minor lags in market reactions, as noted by Fama (1998). Lakonishok and Lee (2001) argue that an extended event window should be included in insider trading studies because even after a trade has been reported, it may take several days for outsiders to become aware of it.

McWilliams and Siegel (1997) recommend an event window of sufficient length to accurately measure the event's impact, yet short enough to avoid confounding effects from nearly coincident events. Brown and Warner (1985) argue that excessively prolonged event windows can weaken the statistical power of the test observer. Consequently, this may lead to unreliable estimations of the event's significance. Therefore, a two-day event window, consisting of the day of the event and one day after, is deemed appropriate for this analysis.

5.1.3 Defining Estimation Window

The estimation window refers to the time interval before the occurrence of the event and is utilized to derive the parameters necessary for predicting normal market returns (MacKinlay, 1997). The literature lacks a definitive consensus on the optimal length of the estimation window. In an example from MacKinlay (1997), he suggested an estimation window of 120 days prior to the event date. MacKinlay further argues that the estimation window must not overlap with the event window to exclude the event's impact on the normal market returns. A sufficient number of observations should also be included in the estimation window to reduce the variance of the cumulative abnormal returns. However, MacKinlay argues that a too-wide estimation window heightens the probability of incorporating similar events within the same period. For our analysis, we have chosen an estimation window of 120 days, starting 130 days prior to the event date and ending ten days before the event date.

5.1.4 Measuring Abnormal Returns

5.1.4.1 Calculating Returns

The returns utilized for the event study in this thesis are determined by computing the percentage change in the closing price between consecutive trading days. The calculations are presented in equation (1):

$$R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} \tag{1}$$

where:

R_{it} = the percentage return for company i on day t

P_{it} = the closing price for company i on day t, and

P_{it-1} = the closing price for company i on day $t-1$

5.1.4.2 Market Model

We calculate the normal returns by employing the market model, which is an economic extension of a statistical single-factor model (MacKinlay, 1997). Furthermore, MacKinlay's framework is developed based on the market model serving as the normal performance return model. He further argues that implementing the single factor eliminates the part of the return related to the market's variation. As a result, this approach reduces the abnormal return and enhances the ability to identify event effects. Additionally, Brown and Warner (1985) determined that the market model is the most suitable approach for event studies, evident from the fact that many prior event studies have utilized this method. Furthermore, they have argued that potential model misspecifications cannot be held accountable for the returns in the model. Hence, we also deem the market model appropriate for our analysis. For company i, the market model is presented as following:

$$E(R_{it}) = \alpha_i + \beta_{it}E(R_{mt}) + \epsilon_{it} \tag{2}$$

where:

R_{it} = the return for company i at time t

R_{mt} = the return for market portfolio m at time t

Alpha (α_i), beta (β_{it}), and ϵ_{it}, where ϵ_{it} has expectation equal to zero, are the parameters of the market model (MacKinlay, 1997). We use the ordinary least squares method to estimate the beta and alpha coefficients, whereby the objective is to minimize the sum of squared differences between the stock and the index (Wooldridge, 2019).

5.1.4.3 Abnormal Returns

The computation of abnormal returns (AR) entails subtracting the expected return based on the market model from the real return in a specified event window of a company i in time t.

$$AR_{it} = R_{it} - E(R_{it}) \tag{3}$$

where:

R_{it} = the return for company i at time t

$E(R_{it})$ = the expected return for company i at time t using the market model

Given our implementation of an event window spanning multiple days, aggregating abnormal returns becomes imperative. Accordingly, the computation of the cumulative abnormal return (CAR) for company i on day t, within the specified event window $[T3, T4]$, can be presented by the following equation:

$$CAR_i[T_3, T_4] = \sum_{t=T3}^{T4} AR_{it} \tag{4}$$

Subsequently, we proceed to compute the cumulative average abnormal returns (CAAR):

$$CAAR_i = \frac{1}{N}\sum_{i=1}^{n} CAR_i \tag{5}$$

5.1.4.4 Variance of Cumulative Average Abnormal Returns

In MacKinlay (1997), it is demonstrated that the abnormal returns condition of the event window will be jointly normally distributed with a zero conditional mean and conditional variance of:

$$\sigma^2(AR_{i\tau}) = \sigma_{\epsilon_i}^2 + \frac{1}{L_1}\left[1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}_m^2}\right] \tag{6}$$

The conditional variance consists of the disturbance variance term and an additional variance due to sampling error in α_i and β_i. According to MacKinlay (1997), the sampling error can cause a serial correlation of abnormal returns even if the true disturbance is independent over time. The length of the estimation window (L_1) determines the proximity of the second term to zero, as it approaches zero with increasing window length. In our study, the estimation window is set at 120 days, so we can assume additional variance to be close to zero and the variance of abnormal return is equal to $\sigma_{\epsilon_i}^2$ and independent over time.

Furthermore, we need to aggregate the variance of abnormal returns for each event period, $\tau = T_3 + 1, \ldots, T_4$. Given N events and large L_1, the sample aggregated variance of abnormal returns is:

$$var(AAR_\tau) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma_\epsilon^2 \tag{7}$$

Last, we will aggregate the variance of average abnormal returns (AAR) over the event window:

$$var\big(CAAR(T_3, T_4)\big) = \sum_{T=T_3}^{T_4} var(AAR_\tau) \tag{8}$$

5.1.4.5 Significance Testing

One can draw inferences regarding the average market reaction by utilizing the parametric test proposed by MacKinlay (1997), as follows:

$$\theta_1 = \frac{CAAR(T_3, T_4)}{\sqrt{var\big(CAAR(T_3, T_4)\big)}} \sim N(0,1) \tag{9}$$

The test can be regarded as a modified version of the standard t-test, incorporating an adjustment employing the estimation window variance. The presented t-test represents the conventional method for evaluating the significance of cumulative abnormal returns (Ding et al., 2018). Kothari et al. (2002) argue that the test statistic described in Equation (9) is appropriately specified, given that an accurate estimation of the variance of one-period mean abnormal return has been achieved.

5.2 Cross-Sectional Regression Analysis

A cross-sectional regression analysis is necessary to establish any causal inferences regarding the relationship between CAR and characteristics. The model definition for such a regression of N observations of abnormal returns and M firm- and/or event characteristics can be defined as the following:

$$CAR_i = \delta_0 + \delta_1 x_{li} + \cdots + \delta_M x_{Mi} + \eta_i \tag{10}$$

$$E(\eta_i) = 0$$

Where CAR represents the abnormal return for the i^{th} observation, while δ_M is the regression coefficient where M ranges from 0 to M. The i^{th} observation's characteristic is represented by x_{Mi}, and the zero-mean disturbance term is expressed by η_i. It should also be noted that η_i is uncorrelated with the $x's$, as outlined in MacKinlay (1997).

5.2.1 Characteristics

We perform a cross-sectional analysis to determine whether the market responds differently to different types of insider trades. To perform this analysis, we identify various characteristics of the trades and firms that may be relevant to the market's response to insider trades.

The characteristics we considered for our analysis include commonly used stock valuation metrics and characteristics associated with insider information. Three objectives guided our selection process. Firstly, we prioritized characteristics that were relevant to the research question. Secondly, we aimed for characteristics that were intuitive and logically connected to stock prices and insider trading. Thirdly, we avoided characteristics that were highly correlated with one another or likely to produce similar outcomes, minimizing the risk of multicollinearity. Ultimately, we arrived at a set of 13 characteristics. By following the three objectives, we ensured that our selected characteristics were reliable, meaningful, and well-suited to our research question.

5.2.1.1 Extraction and Preparation of Data

In the next part, we will describe where we obtain the data for the different characteristics included in the cross-sectional analysis and how we use this data. We divide this section into four parts: Trading data, financial statement data, insider ownership data, and preparation of the data.

Stock trading data

Some of the characteristics described in Chapter 5.2.1.2 are derived using the stock price, market capitalization, number of outstanding shares, or trading volume.[8] These data points are extracted four trading days prior to the announcement date. For example, if an insider trade in Equinor ASA is announced on 25.11.2022 (Friday), the value for the market capitalization of Equinor ASA is extracted on 21.11.2022 (Monday). This gives us a value close to the announcement date while also reducing the chances of a bias of the measured effect in the event window itself. This is because the trade can already be reflected in the variable before our event window, for instance, due to anticipation of the trade. We obtained the daily closing prices for the stocks, market capitalization at close, number of outstanding shares, and daily volume from the Bloomberg Terminal. Bloomberg collects this data from the Oslo Stock Exchange.

Data related to the financial statement

We obtained the data related to the financial statements from the Bloomberg Terminal. Bloomberg collects this data directly from the company's financial reports. Before 2017, companies listed on the Oslo Stock Exchange were obligated to report financial statements four times a year. In 2017, this was changed to two times a year (NOU 2016: 2, p. 16). A survey conducted by the financial newspaper E24 indicated that even though not legally required, most companies still prefer to report their financial results four times a year (Framstad, 2017). Hence, the data related to the financial statements are, for the most part, updated four times a year in connection with the release of the financial statements and a minimum of two times a year. The financial statements data used to calculate some of the characteristics in Chapter 5.2.1.2 are extracted from the same date as the announcement date, as it will not be affected by the insider transaction.[9]

[8] Characteristics that utilize stock trading data: Company Size, Intangible Assets, Altman Z-score, Transaction Size ratio, Insider Ownership ratio, 30-Day Volatility, Price-to-Book, Return on Equity, Enterprise Multiple and Price-to-Earnings.
[9] Characteristics that utilize financial statement data: Intangible Assets, Altman's Z-score, Price-to-Book, Return on Equity, Revenue Growth, Enterprise Multiple and Price-to-Earnings.

Data related to insider ownership

The data relating to the characteristics *Number of Insiders Owning Shares* and the number of outstanding shares held by insiders (*Insider Ownership ratio*) are obtained from the Bloomberg Terminal. Bloomberg collects this data from The Financial Supervisory Authority of Norway, and the data is updated daily. For the same reason as trading data, we extract this data four days prior to the announcement date.

Preparation of the data

In preparation of our data for the cross-sectional regression, we implemented several adjustments to enhance the robustness and accuracy of our analysis. First, we winsorized all characteristics at the 1% interval to address outliers identified in some characteristics. Additionally, before taking the natural logarithm, we added a constant value of plus one to all observations for characteristics that practically cannot be negative. This was necessary to prevent the regression from producing incorrect results or omitting relevant observations. An example is the characteristic Intangible Assets, which has a natural minimum value of zero due to its inability to be negative.[10] However, not all companies have intangible assets, so this characteristic is assigned a missing value by default. Hence, the missing value is correctly set to zero before the log transformation.

5.2.1.2 Description of the Characteristics

Company Size

Company size, where the firm's market capitalization is used as a proxy, is an important characteristic to consider for potential confounding effects on the abnormal return. For instance, the magnitude and significance of the estimated relationship could be impacted by the fact that larger companies are possibly more resilient to the effects of insider trading in comparison to smaller ones. In addition, larger firms have more media and analyst coverage, which can create less information asymmetry (Aussenegg & Ranzi, 2008).

[10] The affected characteristics are: Intangible Assets, Turnover, Altman's Z-score and Insider Ownership ratio.

Turnover

Defined as the average volume of shares traded 10 to 130 days before the announcement date, divided by the number of outstanding shares in that period. Turnover is an interesting metric to consider as it reflects the liquidity of a stock and the investor interest in a company (Eckbo & Norli, 2005). Companies with higher turnover tend to have more investors buying and selling shares, which can impact the stock price. Hence, we anticipate that companies with high turnover will exhibit a higher abnormal return than those with low turnover.

Denoted as:

$$Turnover = \frac{Average\ Daily\ Trading\ Volume\ in\ Period_t}{Average\ Daily\ Outstanding\ Number\ of\ Shares\ in\ Period_t} \tag{11}$$

where:

$t =$ a period of 10 to 130 days before the announcement day

Intangible Assets

This variable includes intangible assets, such as patents, trademarks, brand recognition, and R&D, which are challenging to measure or assess, but offer valuable insights into a company's asset quality and competitive advantages. Goodwill is not included, as we want to focus on a characteristic that emphasizes potential values generated within the firm rather than values realized through acquisitions. An insider purchase in a company with a high share of intangible assets may suggest that the assets are undervalued. Hence, the stock prices of such companies may be more sensitive to insider trades. As described in Chapter 2.4.1 by Coff and Lee (2002), insiders will have more knowledge of the real values of such assets compared to outsiders. An example of this could be a newly developed device or patent that the market is doubtful about, but that the insider, such as the Chief Technical Officer (CTO), has already tested and verified its functionality. Hence, the market may react stronger to insider transactions in companies with a proportion of intangible assets. We scale the intangible assets using market capitalization in order to capture the overall market perception of the company.

Denoted as:

$$Intangible\ Assets = \frac{Total\ Intangible\ Assets - Goodwill}{Market\ Capitalization} \tag{12}$$

Altman's Z-score

Altman's Z-score can serve as a proxy for a company's financial stability. It uses a company's financial statement to calculate a score to predict the probability of becoming insolvent (Kenton, 2022b). A high Altman's Z-score indicates a low probability of bankruptcy, while a low score indicates a high probability of bankruptcy. Companies with higher Altman's Z-score may be more resistant to the effects of insider trading. Conversely, companies with lower Altman's Z-score may be more vulnerable to negative market reactions. Equation (14) is denoted by Altman (1968) in his paper.

Denoted as:

$$Altman's\ Z - score = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E \tag{13}$$

where:

A= Working Capital / Total Assets

B= Retained Earnings / Total Assets

C= Earnings Before Interests and Taxes / Total Assets

D= Market Value of Equity / Total Liabilities

E= Sales / Total Asset

Transaction Size ratio

Another characteristic that we find interesting to examine is the relative size of the transaction. While we have already decided to investigate how various transaction size intervals influence stock prices in the event study, analyzing the relative transaction size could provide a deeper understanding of its impact on the stock price. A large insider purchase in a large company like Equinor ASA may not have as significant impact on the stock price as a similar purchase in a smaller company like Magnora ASA. The transaction size is obtained from the specific insider transaction and scaled with the market capitalization.

Denoted as:

$$Transaction\ Size\ ratio = \frac{Transaction\ Size}{Market\ Capitalization} \quad (14)$$

Number of Insiders Owning Shares

This characteristic measures the number of company insiders who own shares during an insider trade, regardless of the quantity they hold. We believe an increased number of insiders who own shares in a company implies higher confidence and belief in the company's prospects. As a result, we anticipate that more external investors will be prone to purchase shares following an insider's purchase. When numerous insiders hold shares in a company, confidence remains strong even during an insider's sale, and the effect on the stock's return should not be as substantial as it would be if fewer insiders are owning shares.

Insider Ownership ratio

This metric considers the total percentage of outstanding shares held by insiders, unlike the previous metric, which only considers the number of insider shareholders. However, the underlying reasoning is the same, as a high initial percentage of insider ownership suggests that any subsequent changes in ownership may have a relatively smaller impact on the stock price than they would for a company with a lower percentage.

Denoted as:

$$Insider\ Ownership\ ratio = \frac{Total\ Number\ of\ Outstanding\ Shares\ Held\ by\ Insiders}{Total\ Number\ of\ Outstanding\ Shares} \quad (15)$$

30-Day Volatility

Volatility measures the level of variation in stock prices over a specific period, in our case 30 days, and reflects the degree of uncertainty and risk in the market (Hayes, 2022a). Incorporating this characteristic can provide a better understanding of the relationship between volatility and market reactions to insider trading. Companies that experience higher levels of volatility are often associated with greater market risk, which can lead to a higher sensitivity in their stock prices. In contrast, companies with lower levels of volatility may have more stable prices, higher investor confidence, and, therefore, less impact on abnormal returns in cases of insider trading.

Denoted as:

$$\sigma_{30\,days} = \sqrt{252} \times \sqrt{\frac{1}{30} \times \sum_{i=1}^{30} \left(\mu - \ln\left(\frac{Pi}{Pi_{-1}}\right)\right)^2} \tag{16}$$

where:

μ = The average daily log return for the past 30 days

Pi = Stock price on day i

Description of the Characteristics: Valuation and Performance

In the last part of the chapter, we will discuss characteristics related to the firms' relative valuation and performance ("valuation"). We will specifically discuss the price-to-book, return on equity, revenue growth, enterprise multiple, and price-to-earnings. These characteristics serve as common measures used to evaluate a firm's valuation, each offering a distinct perspective. We will apply the same reasoning across all the characteristics discussed below. In summary, when a company has a low valuation, an insider purchase is expected to have a more pronounced impact on abnormal returns compared to a company with a high valuation. Conversely, the effect will be stronger for insider sales when the company's valuation is high rather than low. This intuition is based on two underlying reasons.

Firstly, when a company has a strong valuation, an insider's purchase is generally viewed positively as it confirms market beliefs. However, it may not provide new information compared to a situation with a low valuation, thereby eliciting a weaker market reaction. Conversely, an insider sale in a company with a low valuation merely confirms existing market beliefs, while an insider sale in a company with a high valuation can potentially provide new information and elicit a stronger market reaction.

Secondly, a high valuation may leave limited room for improvement, resulting in a weaker market reaction to an insider purchase. In contrast, an insider purchase in a company with a low valuation, which has a larger potential for improvement, can generate a stronger market response. Furthermore, the impact of an insider sale in a company with a low valuation is generally weaker, as it represents a limited downside, whereas an insider sale in a company with a high valuation carries a larger downside and thus may result in a stronger market reaction.

Price-to-Book

The Price-to-Book ratio is a commonly used measure of a company's valuation and is often considered a proxy for market expectations of future earnings and growth prospects (Fernando, 2022). The market price per share represents the stock's closing price, while the book value of equity per share is calculated by dividing the company's total book value of equity by the number of outstanding shares.

Denoted as:

$$Price\ to\ Book = \frac{Market\ Price\ Per\ Share}{Book\ Value\ of\ Equity\ Per\ Share} \tag{17}$$

Return on Equity

The Return on Equity metric evaluates a company’s profitability by assessing its net income relative to its shareholders’ equity (Fernando, 2023). We want to investigate how a company's profitability impacts stock prices during insider trading.

Denoted as:

$$Return\ on\ Equity = \frac{Net\ Income}{Market\ Capitalization} \tag{18}$$

Revenue Growth

The Revenue Growth metric indicates whether a company's revenue has increased or decreased over time, reflecting its capacity to grow sales and expand its business operations. It is measured as the year-over-year growth by comparing the current period with the same period the prior year. When a company lacks any previously reported figures, the characteristic is assigned a zero value.

Denoted as:

$$Revenue\ Growth\ = \frac{Current\ Year's\ Revenue}{Previous\ Year's\ Revenue}\ -\ 1 \tag{19}$$

Enterprise Multiple

The metric EV/EBITDA, known as "Enterprise Multiple", is a measure of a company's valuation, which evaluates its enterprise value (EV) relative to its earnings before interests, taxes, depreciation, and amortization (EBITDA). The Enterprise Multiple is commonly used to measure a company's ability to generate earnings and evaluate its relative value compared to other companies within the same industry (Hayes, 2022b).

Denoted as:

$$Enterprise\ Multiple = \frac{Market\ Capitalization + EV\ Components}{EBITDA\ Adjusted} \tag{20}$$

where:

EV Components =	Preferred Equity + Minority Interest + Net Debt – Nominal Amount of Debt Included in Price – Other Enterprise Value Adjusted
EBITDA Adjusted =	Adjusted Operating Income + Depreciation & Amortization + Operating Lease Expense Adjustment (if applicable)

Price-to-Earnings

The Price-to-Earnings ratio is a valuation metric that compares a company's stock price to its earnings per share.[11] The metric measures the price investors are willing to pay for each dollar of earnings and is frequently used to assess the relative value of companies in the same industry (Kenton, 2022c).

Denoted as:

$$Price\ to\ Earnings = \frac{Stock\ Price}{Earnings\ Per\ Share} \tag{21}$$

where:

Earnings Per Share = Trailing 12 months earnings per share before extraordinary item

[11] Although the Price-to-Earnings multiple and the Enterprise Multiple are somewhat similar, we want to examine how the profitability of the firm affects CAR both when accounting for the firm's capital structure and not.

6 Analysis

This section will present the findings from our event study and cross-sectional regression analysis. As mentioned in the introduction, we have the following main research question which we aim to address:

> *What impact does transaction size, insider position, industry, and specific event and firm characteristics have on the magnitude and significance of the market's response to legal insider trading?*

6.1 Short-Term Market Reactions to Insider Trading

In the subsequent section, we shall investigate the short-term market responses to insider trading. First, we will present two figures showing the daily abnormal returns. Then we will present the findings for the entire sample and the transaction sizes. Next, we will examine the impact of the insider's position. Finally, we will analyze how the industry of the companies affects market reactions.

Figure 3 below presents the average abnormal return (AAR) over a period of ten days before the announcement of the insider transaction and ten days after for the whole sample. This figure indicates that the AAR for purchases increases rapidly on the event day and drops two days after. For insider sales, we see no clear pattern around the event day. There are more fluctuations than for insider purchases, which may be caused by the lower number of observations, combined with the possibility of a weaker market reaction to insider sales.

Furthermore, Figure 4 below presents the CAAR over a period of two days before and ten days after the announcement of the insider trade.[12] As expected for insider purchases, we see an increase on the announcement day and the day after. The CAAR then stays high and steady for the remaining ten days. As for insider sales, we see a negative development of the cumulative abnormal return. Although this is also as expected, the negative abnormal returns start on the day before the announcement day. A possible explanation is that some insider sales may have been anticipated before the announcement day. This argument is strengthened by the fact that insider sales are on average larger in terms of transaction size (as seen in Chapter 4.4), and may be connected to dismissals of positions.

[12] See Figure 5 and 6 in Appendix B for a histogram of the distribution of the cumulative abnormal return for each event in the main event window.

Figure 3: Daily Average Abnormal Return (AAR)

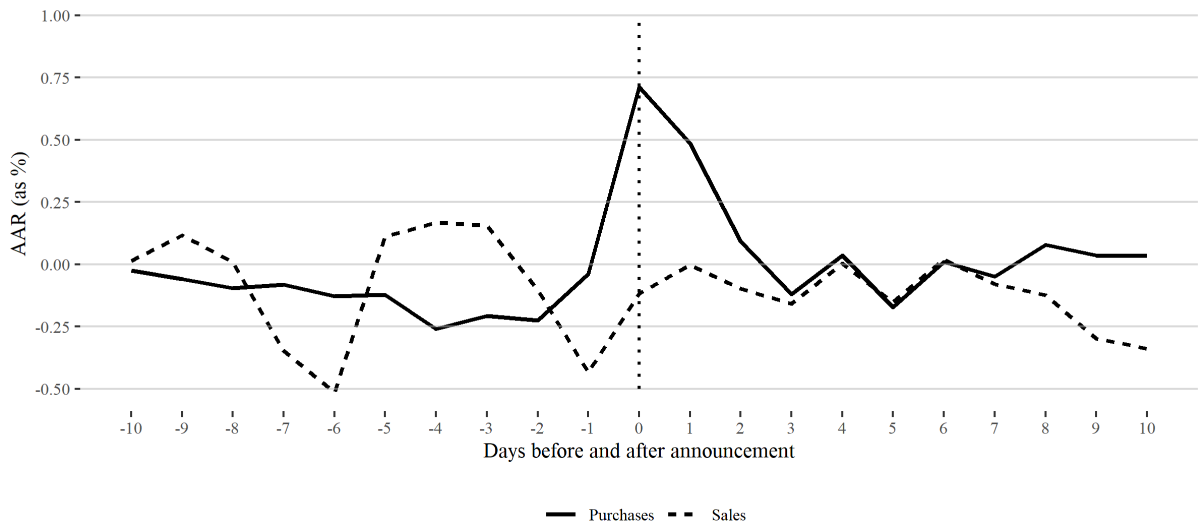
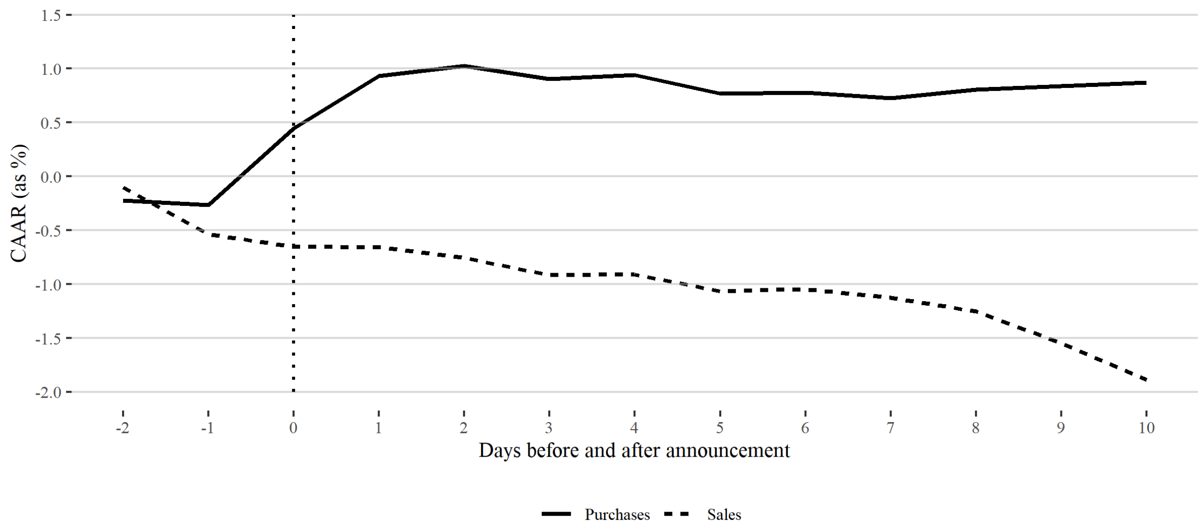


Figure 4: Daily Cumulative Average Abnormal Return (CAAR)



6.1.1 Market Reactions to Insider Trading: Full Sample and Transaction Size

Table 3 examines the CAAR following insider trades for companies on the Oslo Stock Exchange. The table has been classified into purchases and sales. Moreover, the panels present the CAAR for the full sample and for small, medium, and large transactions.

Table 3: CAAR from Insider Trades Categorized by Transaction Size

The presented table displays the CAAR for insider trades, categorized by transaction size. The analysis covers all insider trades reported between 01.01.2017 and 31.12.2022, with a minimum transaction size of NOK 100,000. The main event window is set to [0, 1], and the robustness of the findings is tested by considering additional event windows. CAAR is estimated using the market model over the period [-130, -10]. Panel A in the table outlines CAARs for insider purchases, while Panel B presents CAARs for insider sales. The panels present the CAARs for the entire sample and for sub-samples of small, medium, and large transactions. Small transactions refer to trades valued below NOK 500,000, medium transactions to those between NOK 500,000 and NOK 5,000,000, and large transactions to those valued over NOK 5,000,000.

CAAR [Panel A: Purchases]

	[-2, 0]	[-2, 1]	[-2, 2]	[-1, 0]	[-1, 1]	[-1, 2]	[0, 1]	[0, 2]
All	0.41%***	0.87%***	0.95%***	0.63%***	1.09%***	1.18%***	1.14%***	1.22%***
N=2033	(0.111)	(0.129)	(0.144)	(0.091)	(0.111)	(0.129)	(0.091)	(0.111)
Small	0.04%**	0.39%***	0.54%*	0.21%*	0.56%***	0.70%***	0.76%***	0.91%***
N=1032	(0.154)	(0.178)	(0.199)	(0.126)	(0.154)	(0.178)	(0.126)	(0.154)
Medium	0.67%***	1.20%***	1.14%***	0.93%***	1.46%***	1.40%***	1.37%***	1.31%***
N=709	(0.192)	(0.221)	(0.247)	(0.156)	(0.192)	(0.221)	(0.156)	(0.192)
Large	1.05%***	1.76%***	1.94%***	1.40%***	2.11%***	2.29%***	1.92%***	2.10%***
N=292	(0.297)	(0.343)	(0.384)	(0.243)	(0.297)	(0.343)	(0.243)	(0.297)

CAAR [Panel B: Sales]

	[-2, 0]	[-2, 1]	[-2, 2]	[-1, 0]	[-1, 1]	[-1, 2]	[0, 1]	[0, 2]
All	-0.68%**	-0.65%*	-0.71%*	-0.51%**	-0.48%	-0.55%	-0.03%	-0.10%
N=386	(0.301)	(0.348)	(0.389)	(0.246)	(0.301)	(0.348)	(0.246)	(0.301)
Small	1.26%**	2.23%***	2.40%***	0.98%**	1.95%***	2.12%***	1.45%***	1.63%***
N=107	(0.580)	(0.670)	(0.749)	(0.474)	(0.580)	(0.670)	(0.474)	(0.580)
Medium	-1.48%***	-1.36%***	-1.06%*	-1.16%***	-1.04%**	-0.74%	-0.35%	-0.05%
N=178	(0.438)	(0.506)	(0.565)	(0.358)	(0.438)	(0.506)	(0.358)	(0.438)
Large	-1.31%**	-2.43%***	-3.40%***	-0.96%*	-2.07%***	-3.04%***	-1.06%**	-2.03%***
N=101	(0.594)	(0.686)	(0.767)	(0.485)	(0.594)	(0.686)	(0.485)	(0.594)

Standard errors in parentheses and reported in same unit as CAAR.

**p<0.10, **p<0.05, ***p<0.01*

6.1.1.1 Full Sample

In Panel A in Table 3 for the full sample (All), insider purchases exhibit positive and highly statistically significant coefficients across all eight event windows. Most of them are approximately of equal magnitude, except for windows [-2, 0] and [-1, 0] yielding the lowest effect with 0.41 and 0.63 percent, respectively. The largest effect is found in the event window [0, 2] with a cumulative average abnormal return (CAAR) of 1.22 percent. This is slightly higher than our main event window, [0, 1], yielding 1.14 percent. Another observation is that the effects are stronger the fewer days are included before and the more days are included after the announcement date. This is intuitive, as the effect of the insider trade is expected to take place on or after the announcement day and not before.

Further, only half of the coefficients are statistically significant for insider sales in Panel B for the full sample (All), but only at the 5 and 10 percent level. As expected, all coefficients are negative for the full sample. The main event window [0, 1] yields the lowest effect of only -0.03 percent, and the effect is not statistically significant. The highest effects are seen in the event window [-2, 2] with a CAAR of -0.71 percent. As discussed above in relation to Figure 4, there seems to be a notable negative abnormal return on the day before the announcement day. This effect is captured in all event windows except for the event windows [0, 1] and [0, 2] as these two windows do not include the day before the announcement day. The results for insider sales are also affected by the unexpectedly large positive coefficients in the category for smaller sales, which will be covered later in this chapter.

Overall, our finding aligns with the results reported by Fidrmuc et al. (2006), who found a positive coefficient of 1.16% for purchases and a negative coefficient of 0.26% for sales in the same event window [0, 1]. Lakonishok and Lee (2001) concluded that insider purchases give positive signals about further price development, which could not be shown to be the case for insider selling. According to them, this can potentially be explained by incentives for sales which are linked to a diversification motive, while the profit motive was strongest when purchasing stocks in the company. Schotland (1967) also argued that the market reacted quickly when insiders purchased securities but had a small initial price effect when insiders sold securities.

Hypothesis I state that *insider trades on the Oslo Stock Exchange cause short-term abnormal returns.* Our findings support this hypothesis for insider purchases, but not for insider sales.

6.1.1.2 Transaction Size

In Panel A in Table 3, insider purchases exhibit positive and highly statistically significant coefficients across all eight event windows for all transaction sizes. Large insider purchases exhibit the strongest effect on CAAR, followed by medium purchases and then small purchases, yielding the lowest effect on CAAR. Specifically for our main event window [0, 1], the effect on CAAR is more than twice as high for large purchases (1.92 percent) compared to small purchases (0.76 percent). Our findings are supported by Betzer and Theissen (2009), who argue that larger transactions should provide a stronger signal to the market.

For insider sales in Panel B, we observe ambiguous results. The effect on CAAR is negative for all large and medium sales, with a stronger effect for large sales. Only the coefficients for large and small insider sales are statistically significant across all event windows. During data collection on insider trades, we observed several large sales transactions associated with insiders' dismissal from the firm. Intuitively, we believe that the market reacted strongly to these dismissals since new management may lead to uncertainty in the firm. The announcement of the dismissal and the announcement of the insider sale may not be published on the same day, causing the larger event window [-2, 2] to pick up this unalignment, hence yielding the strongest response of -3.40 percent.

While larger sales exhibiting stronger effects on CAAR is intuitive, considering the market signal being stronger related to larger sales (as found for purchases), economic intuition suggests that all coefficients for sales should be negative since insider sales can be interpreted as negative signals to the market. This argument is supported by Lorie and Niederhoffer (1968) and Chowdhury et al. (1993), who demonstrated that purchases tend to be followed by additional purchases, while additional sales follow sales. However, unexpected statistically significant positive coefficients are observed for small sales. To further investigate this, we examined all 107 insider sales in the small category. No negative CARs below 15 percent were found, but several positive CARs exceeding 15 percent were identified, with the highest being 86 percent. Further analysis revealed that five trades, which exhibited unusually large positive CARs above 15 percent, coincided with unrelated events such as successful private placements, strong quarterly earnings, and refinancing achievements.[13] When excluding these five observations, the mean of the remaining cumulative abnormal returns is calculated to be slightly below zero for all event windows, as expected.

[13] Refer to Table 10 in Appendix B for detailed information on these five trades.

Hypothesis II states that *the market's reactions to insider trades on the Oslo Stock Exchange are stronger for larger transaction sizes than smaller transaction sizes*. Our findings support this hypothesis for insider purchases, but not for insider sales.

6.1.2 Market Reactions to Insider Trading: Position within the Company

Table 4 examines the CAAR for companies on the Oslo Stock Exchange based on the hierarchical position of insiders. The table is categorized into two sections, namely purchases and sales. Each panel present the CAAR categorized by positions within the company. Specifically, CEO, CFO, other C-suits, chair, board members, stakeholders, and others.

Table 4: CAAR from Insider Trades Categorized by Position

The presented table displays the Cumulative Average Abnormal Returns (CAARs) for insider trades, categorized by the position held by the insider within the firm. The analysis covers all insider trades reported between 01.01.2017 and 31.12.2022, with a minimum transaction size of NOK 100,000. The main event window is set at [0, 1], and the robustness of the findings is tested by considering additional event windows. CAAR is estimated using the market model over the period [-130, -10].

CAAR [Panel A: Purchases]								
	[-2, 0]	[-2, 1]	[-2, 2]	[-1, 0]	[-1, 1]	[-1, 2]	[0, 1]	[0, 2]
CEO	0.35%***	1.07%***	1.17%***	0.60%**	1.32%***	1.42%***	1.62%***	1.73%***
N=376	(0.257)	(0.297)	(0.332)	(0.210)	(0.257)	(0.297)	(0.210)	(0.257)
CFO	-1.99%***	-1.22%**	-1.05%*	-1.40%***	-0.63%	-0.46%	0.32%	0.49%
N=114	(0.480)	(0.554)	(0.620)	(0.392)	(0.480)	(0.554)	(0.392)	(0.480)
Other C-suits	1.33%*	1.36%	2.09%**	1.27%**	1.30%*	2.04%**	1.88%***	2.61%***
N=57	(0.738)	(0.853)	(0.953)	(0.603)	(0.738)	(0.853)	(0.603)	(0.738)
Chair	0.87%***	1.51%***	1.59%***	0.76%***	1.40%***	1.47%***	1.46%***	1.54%***
N=351	(0.256)	(0.296)	(0.331)	(0.209)	(0.256)	(0.296)	(0.209)	(0.256)
Board members	0.78%***	1.11%***	1.12%***	0.98%***	1.32%***	1.32%***	0.91%***	0.92%***
N=628	(0.198)	(0.228)	(0.255)	(0.162)	(0.198)	(0.228)	(0.162)	(0.198)
Stakeholders	0.23%*	0.84%**	1.25%**	0.77%***	1.38%***	1.80%***	1.57%***	1.99%***
N=197	(0.400)	(0.462)	(0.517)	(0.327)	(0.400)	(0.462)	(0.327)	(0.400)
Others	0.26%	0.49%	0.41%	0.59%***	0.82%***	0.74%**	0.93%***	0.85%***
N=310	(0.268)	(0.309)	(0.346)	(0.219)	(0.268)	(0.309)	(0.219)	(0.268)

Standard errors in parentheses and reported in the same unit as CAAR.

$^*p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

CAAR [Panel B: Sales]

	[-2, 0]	[-2, 1]	[-2, 2]	[-1, 0]	[-1, 1]	[-1, 2]	[0, 1]	[0, 2]
CEO	1.45%	0.66%	0.36%	0.54%	-0.25%	-0.55%	-0.32%	-0.62%
N=24	(1.054)	(1.217)	(1.360)	(0.860)	(1.054)	(1.217)	(0.860)	(1.054)
CFO	-0.83%	-1.02%	-1.43%	-0.57%	-0.76%	-1.17%	-0.33%	-0.74%
N=34	(0.973)	(1.124)	(1.257)	(0.795)	(0.973)	(1.124)	(0.795)	(0.973)
Other C-suit	-0.56%	-0.90%	-0.06%	-0.72%	-1.06%	-0.22%	-1.13%*	-0.29%
N=25	(0.707)	(0.816)	(0.912)	(0.577)	(0.707)	(0.816)	(0.577)	(0.707)
Chair	-2.61%**	-2.81%*	-3.12%*	-1.78%*	-1.98%	-2.28%	-0.85%	-1.15%
N=21	(1.183)	(1.366)	(1.527)	(0.966)	(1.183)	(1.366)	(0.966)	(1.183)
Board member	-1.38%**	-0.46%	-0.42%	-1.00%*	-0.07%	-0.04%	0.91%*	0.94%
N=123	(0.619)	(0.714)	(0.799)	(0.505)	(0.619)	(0.714)	(0.505)	(0.619)
Stakeholder	1.62%	0.97%	0.15%	0.88%	0.23%	-0.59%	0.65%	-0.18%
N=15	(1.406)	(1.624)	(1.816)	(1.148)	(1.406)	(1.624)	(1.148)	(1.406)
Other	-0.26%	-0.79%	-0.94%*	-0.24%	-0.77%*	-0.93%*	-0.82%**	-0.97%**
N=144	(0.414)	(0.478)	(0.534)	(0.338)	(0.414)	(0.478)	(0.338)	(0.414)

Standard errors in parentheses and reported in the same unit as CAAR.

**p<0.10, **p<0.05, ***p<0.01*

Insider purchases in Panel A in Table 4 yield positive and statistically significant coefficients across almost all categories. These findings align with Seyhun's (1986) study, which also observed positive coefficients across all positions within the company.[14] While all coefficients are positive for the main event window [0, 1] and the event window [0, 2], this is not the case for the remaining event windows.

Purchases made by the *CFO* exhibit unexpected negative coefficients. The effect is strongest for the windows that include the least number of days after the announcement day, and the most days before. This finding is however not economically intuitive, as we would expect insider sales made by the *CFO* to exhibit strong positive coefficients, almost as high as for the *CEO*, due to both having access to key financial information. By investigating the CARs in this category, as we did for small insider sales in Chapter 6.1.1, we found that a few trades coincided with other unrelated negative events in the days before the announcement date. Given the low number of observations (114), only a few extreme values can affect the CAAR strongly. This limitation is further highlighted in Chapter 8.

[14] Seyhun (1986) employs cumulative daily average prediction errors, whereas we use CAAR. He found that top executives had a 3.4 percent abnormal return in the 30 trading days following a purchase transaction, compared to only 0.9 percent for other insiders.

The results for the category *other C-suit* are somewhat unexpected given the significantly higher coefficients compared to the *CEO*. While this might be due to coinciding positive unrelated events, given the low number of observations (57), we argue that specific chief officers have access to key information within their area of expertise, possibly generating larger market reactions than for more general roles such as the CEO. Furthermore, Jeng et al. (2003) argue that insiders with higher positions are more likely to be carefully scrutinized by shareholders and regulators and, therefore, reluctant to trade on this informational advantage. This might explain why the effect is larger for *other C-suits* than for *CEO*, given the CEO's higher position within the company.

Despite the unexpected results for *CFO*, insider purchases in Panel A in Table 4 provide evidence that market reactions to insider trades are more pronounced for insiders occupying higher positions within the firm. Particularly, the coefficients for the *CEO*, *other C-suit*, and *chair* exhibit a larger magnitude than the lower levels of the position hierarchy, such as *other* and *board member*. This observation can potentially be explained by the fact that outside investors may interpret transactions from insiders holding higher positions as more valuable in terms of information revelation, and consequently act upon these insider trades. This view is consistent with the arguments presented by Seyhun (1986) and Fidrmuc et al. (2006), who suggest that higher positions in the job hierarchy imply greater access to information and a higher potential for additional returns.

Unlike the coefficients for insider purchases in Panel A, we observe fewer statistically significant coefficients for insider sales in Panel B. Only a few coefficients are statistically significant at 5 and 10 percent significance levels. Of all the statistically significant coefficients, the strongest effect is found for *chair* in the event window [-2, 2], yielding -3.12 percent, and the weakest effect is found for the category o*thers* in the event window [-1, 1] with -0.77 percent. A common factor for all categories is the low number of observations, making it difficult to conclude anything. As presented in Chapter 6.1.1, we found no statistically significant evidence that the full sample for insider sales generates abnormal returns. The fact that we now split this sample into seven subcategories makes the findings in Panel B in Table 4 less surprising.

There is no clear pattern in whether sales by insiders with higher positions within the firm trigger larger price reactions. The absence of such a pattern is consistent with Jeng et al. (2003), who found that trades by top executives do not generate abnormal returns.[15] Betzer and Theissen (2009) came to a similar conclusion, arguing that the insider's position does not have a noticeable effect on CAR, as their findings were not statistically significant. One plausible explanation for the results in Panel B is that insider sales may lack the informative value compared to insider purchases. Seyhun (1998) suggests that insider sales may be motivated by liquidity concerns, such as rebalancing portfolios or obtaining personal liquidity, rather than purely profit-maximizing motives.[16]

Hypothesis III states that *the market reactions to insider trading on the Oslo Stock Exchange are stronger for insiders with a higher position in the company than those with a lower position*. Our findings support this hypothesis for insider purchases, but not for insider sales.

6.1.3 Market Reactions to Insider Trading: Industries

Table 5 examines the cumulative abnormal returns (CAAR) of insider trades within eleven different industries on the Oslo Stock Exchange. The table is divided into two panels, each displaying the CAAR resulting from insider purchases and sales. Furthermore, the panels exhibit the CAARs using the Global Industry Classification Standard (GICS): Communication Services, Consumer Discretionary, Consumer Staples, Energy, Financials, Health Care, Industrials, Information Technology, Materials, Real Estate, and Utilities.

[15] Jeng et al. (2003) studied the US market between 1975 and 1996. They categorized insiders as top executives, officers, and directors, which differed slightly from the categorization in our thesis.
[16] Motivations for insider trading is further discussed in Chapter 2.1

Table 5: CAAR from Insider Trades Categorized by Industry

The presented table displays the Cumulative Average Abnormal Returns (CAAR) for insider trades, categorized by industry. The analysis covers all insider trades reported between 01.01.2017 and 31.12.2022, with a minimum transaction size of NOK 100,000. The event window is primarily set at [0, 1], and the robustness of the findings is tested by considering additional event windows. CAAR is estimated using the market model over the period [-130, -10].

CAAR [Panel A: Purchases]

	[-2, 0]	[-2, 1]	[-2, 2]	[-1, 0]	[-1, 1]	[-1, 2]	[0, 1]	[0, 2]
Communication Services	-1.52%**	-1.59%**	-1.14%	-1.19%**	-1.26%**	-0.81%	-0.32%	0.14%
N=53	(0.606)	(0.699)	(0.782)	(0.494)	(0.606)	(0.699)	(0.494)	(0.606)
Consumer Discretionary	-0.12%	0.30%	0.41%	0.40%	0.82%	0.94%	1.10%**	1.21%**
N=94	(0.564)	(0.651)	(0.728)	(0.461)	(0.564)	(0.651)	(0.461)	(0.564)
Consumer Staples	-1.64%***	-1.57%***	-1.25%**	-0.73%**	-0.67%	-0.34%	0.22%	0.54%
N=105	(0.423)	(0.488)	(0.546)	(0.345)	(0.423)	(0.488)	(0.345)	(0.423)
Energy	0.48%	1.05%***	1.19%***	0.67%**	1.24%***	1.38%***	1.40%***	1.54%***
N=319	(0.329)	(0.380)	(0.424)	(0.268)	(0.329)	(0.380)	(0.268)	(0.329)
Financials	-0.17%	-0.09%	-0.40%**	0.10%	0.17%	-0.14%	0.28%**	-0.03%
N=370	(0.155)	(0.179)	(0.200)	(0.127)	(0.155)	(0.179)	(0.127)	(0.155)
Health Care	1.38%**	2.40%***	2.35%***	1.75%***	2.77%***	2.73%***	2.51%***	2.47%***
N=115	(0.639)	(0.738)	(0.826)	(0.522)	(0.639)	(0.738)	(0.522)	(0.639)
Industrials	1.32%***	1.95%***	1.97%***	1.50%***	2.13%***	2.15%***	1.95%***	1.97%***
N=412	(0.260)	(0.300)	(0.335)	(0.212)	(0.260)	(0.300)	(0.212)	(0.260)
Information Technology	1.08%***	1.75%***	2.13%***	1.06%***	1.73%***	2.12%***	1.54%***	1.92%***
N=421	(0.258)	(0.298)	(0.333)	(0.211)	(0.258)	(0.298)	(0.211)	(0.258)
Materials	-0.24%	0.19%	0.24%	-0.33%	0.10%	0.16%	0.36%	0.42%
N=60	(0.663)	(0.765)	(0.856)	(0.541)	(0.663)	(0.765)	(0.541)	(0.663)
Real Estate	-0.04%	-0.06%	0.38%	0.30%	0.28%	0.72%	0.01%	0.44%
N=58	(0.481)	(0.555)	(0.621)	(0.392)	(0.481)	(0.555)	(0.392)	(0481)
Utilities	-1.67%*	0.51%	0.81%	-1.31%*	0.87%	1.17%	1.21%	1.51%
N=26	(0.908)	(1.048)	(1.172)	(0.741)	(0.908)	(1.048)	(0.741)	(0.908)

Standard errors in parenthesis and reported in the same unit as CAAR.

**p<0.10, **p<0.05, ***p<0.01*

CAAR [Panel B: Sales]

	[-2, 0]	[-2, 1]	[-2, 2]	[-1, 0]	[-1, 1]	[-1, 2]	[0, 1]	[0, 2]
Communication Services	2.50%	2.31%	0.76%	2.39%*	2.20%	0.66%	2.06%	0.52%
N=9	(1.361)	(1.571)	(1.757)	(1.111)	(1.361)	(1.571)	(1.111)	(1.361)
Consumer Discretionary	-3.09%*	-3.11%*	-3.32%	-1.80%	-1.82%	-2.03%	-0.61%	-0.82%
N=41	(1.559)	(1.800)	(2.012)	(1.273)	(1.559)	(1.800)	(1.273)	(1.559)
Consumer Staples	-1.39%	-1.44%	-2.14%	-0.63%	-0.69%	-1.39%	0.10%	-0.60%
N=17	(1.208)	(1.395)	(1.560)	(0.987)	(1.208)	(1.395)	(0.987)	(1.208)
Energy	-2.58%***	-1.85%**	-1.61%*	-2.83%***	-2.10%***	-1.86%**	0.42%	0.66%
N=64	(0.723)	(0.835)	(0.933)	(0.590)	(0.723)	(0.835)	(0.590)	(0.723)
Financials	-0.44%	-0.65%	-0.84%	-0.61%*	-0.83%**	-1.02%**	-0.67%**	-0.86%**
N=53	(0.399)	(0.461)	(0.516)	(0.326)	(0.399)	(0.461)	(0.326)	(0.399)
Health Care	1.10%	0.77%	0.79%	1.05%	0.73%	0.75%	0.40%	0.42%
N=25	(1.097)	(1.267)	(1.416)	(0.896)	(1.097)	(1.267)	(0.896)	(1.097)
Industrials	-0.85%	-1.39%**	-1.31%*	-0.63%	-1.16%*	-1.08%	-1.41%***	-1.33%**
N=69	(0.586)	(0.677)	(0.757)	(0.479)	(0.586)	(0.677)	(0.479)	(0.586)
Information Technology	-1.36%*	-1.66%*	-1.64%*	-1.39%**	-1.68%**	-1.67%*	-1.33%**	-1.32%*
N=54	(0.737)	(0.851)	(0.952)	(0.602)	(0.737)	(0.851)	(0.602)	(0.737)
Materials	-1.27%*	-1.50%*	-1.77%**	-0.59%	-0.83%	-1.09%	-0.36%	-0.62%
N=30	(0.656)	(0.758)	(0.847)	(0.536)	(0.656)	(0.758)	(0.536)	(0.656)
Real Estate	14.18%***	16.33%***	15.48%***	13.05%***	15.20%***	14.35%***	8.62%***	7.77%***
N=17	(1.914)	(2.210)	(2.471)	(1.563)	(1.914)	(2.210)	(1.563)	(1.914)
Utilities	1.83%	0.43%	0.69%	1.39%	-0.01%	0.26%	-1.54%	-1.27%
N=7	(1.757)	(2.029)	(2.268)	(1.435)	(1.757)	(2.029)	(1.435)	(1.757)

Standard errors in parentheses and reported in the same unit as CAAR.

**p<0.10, **p<0.05, ***p<0.01*

As expected, based on the results in Chapter 6.1.1 for the full sample, most of the coefficients in Panel A in Table 5 are positive, with only a few exceptions. The smallest effect is observed for Real Estate during the main event window [0, 1], at 0.01 percent, while the largest effect in absolute value is observed in *Health Care* during the event window [-1, 1] at 2.77 percent. For the main event window [0, 1], the largest coefficient observed is also for *Health Care* at 2.51 percent. As for robustness, we find that most coefficients within each category exhibit relatively similar magnitude across all event windows.

Most notably, and as hypothesized, some of the largest effects seem to come from companies operating in R&D-intense industries, namely *Health Care* and *Information Technology*. According to Coff and Lee (2002), insider trading is particularly informative in R&D-intensive companies due to the unpredictability of outcomes associated with many R&D projects.

Therefore, whenever an insider purchase occurs within an R&D-intensive company, outside investors may interpret it as a signal of favorable R&D outcomes and react accordingly, leading to a significantly positive price reaction. In addition, we see relatively large coefficients in the main event window [0, 1] for *Energy* and *Industrials*, yielding 1.40 and 1.95 percent, respectively. This finding is somewhat consistent with Cheuk et al. (2006), who also found that firms in Industrials generated statistically significant and persistent abnormal returns.[17]

For insider sales in Panel B, the most notable observation is the *Real Estate* industry. This industry exhibits values with much larger coefficients than the other industries, and the coefficients are all statistically significant. We are observing such large coefficients due to the positive news announced by KMC, a real estate firm, during the event window of insider trades in our dataset.[18] Additionally, due to the small number of observations in this industry, the CAAR may be heavily influenced by these outside events.

Only some of the coefficients are statistically significant for the remaining industries, not including *Real Estate*. The low number of observations in most categories may heavily impact the results. However, the statistically significant coefficients exhibit negative abnormal returns across all event windows. The strongest significant effect in the main event window [0, 1] is found for Industrials, yielding -1.41 percent. Furthermore, the coefficients in *Health Care* and *Information Technology* do not stand out significantly in terms of the magnitude for insider sales as they do for insider purchases. Thus, our previous argument that R&D-intensive industries experience larger CAAR coefficients for insider trades is not valid in the case of insider sales.

Hypothesis IV states that *market reactions to insider trades on the Oslo Stock Exchange are stronger for R&D-intense firms than non-R&D-intense firms*. Our findings support this hypothesis for insider purchases, but not for insider sales.

[17] Cheuk et al. (2006) used four different event windows [-20, -1], [1, 5], [1, 10] and [1, 20]. The coefficient for the event window [-20, -1] was negative, but the rest of the coefficients in Industrials were positive and larger compared to the other industries.

[18] Refer to Table 10 in the Appendix B for more details on the external events that had an impact on the abnormal returns during the event window of the trades.

6.2 Cross-Sectional Regression Analysis

Table 6 displays the CAR within the main event window [0, 1]. The table contains four models represented by columns (1) through (4). Columns (1) and (2) present a cross-sectional analysis with observations on sales and purchases greater than NOK 100,000, respectively, excluding the characteristics Enterprise Multiple and Price-to-Earnings. Columns (3) and (4) present a cross-sectional analysis with observations on sales and purchases greater than NOK 100,000, respectively, including the characteristics Enterprise Multiple and Price-to-Earnings. The number of observations decreases in columns (3) and (4) due to excluding any observations with missing values for the characteristics Enterprise Multiple and Price-to-Earnings. As a result, the sample size is reduced in these models, leading to fewer observations.

Palmer (2021) suggests that missing values may occur in cases where companies are recently listed and lack previous data or have negative price-to-earnings values. Negative price-to-earnings values can arise from negative earnings per share. Palmer states that although negative price-to-earnings ratios are mathematically possible, they are generally not accepted by the financial community. In the data set from Bloomberg, there are no negative price-to-earnings values, indicating that Bloomberg does not include negative values for this specific characteristic. Intuitively, this also applies to the enterprise multiple (EV/EBITDA).

The next section will provide a detailed examination of each characteristic presented in Table 6. Log-transforming some of the characteristics allows for a level-log interpretation.

Table 6: Cross-Sectional Regression with Main Event Window [0,1]

The table contains four models represented by columns (1) through (4). Columns (1) and (2) present a cross-sectional analysis with observations on sales and purchases, respectively, excluding the characteristics Enterprise Multiple and PE. Columns (3) and (4) present a cross-sectional analysis with observations on sales and purchases, respectively, including the characteristics Enterprise Multiple and Price-to-Earnings. The event period is set to the announcement day and one day after.

	Dependent variable:			
	CAR [0, 1]			
	(1: Sale)	(2: Purchase)	(3: Sale)	(4: Purchase)
ln(Company Size)	−1.055***	−0.518***	−0.850**	−0.556***
	(0.348)	(0.135)	(0.422)	(0.172)
ln(Turnover)	−0.248	0.316**	−0.331	0.365**
	(0.373)	(0.140)	(0.404)	(0.172)
ln(Intangible Assets)	0.456	3.489***	4.872	2.634*
	(5.904)	(1.220)	(5.944)	(1.419)
ln(Altman's Z-score)	0.083	0.096	0.750	0.456
	(0.554)	(0.137)	(0.698)	(0.301)
ln(Transaction Size ratio)	−0.379*	0.422***	−0.556**	0.416***
	(0.219)	(0.086)	(0.245)	(0.107)
Number of Insiders Owning Shares	0.085	0.082***	0.085	0.064*
	(0.086)	(0.028)	(0.094)	(0.036)
ln(Insider Ownership ratio)	−0.960*	−0.600***	0.171	−0.858***
	(0.507)	(0.200)	(0.599)	(0.281)
ln(30-Day Volatility)	0.225	0.859***	−0.071	0.353
	(0.814)	(0.326)	(0.953)	(0.457)
Price-to-Book	−0.055	−0.245	−0.388	−0.197
	(0.576)	(0.254)	(0.639)	(0.376)
Return on Equity	−0.033*	0.010**	−0.057***	−0.001
	(0.018)	(0.005)	(0.020)	(0.008)
Revenue Growth	−0.006	−0.002**	−0.002	−0.002
	(0.007)	(0.001)	(0.008)	(0.001)
Enterprise Multiple			−0.020	−0.021***
			(0.032)	(0.006)
Price-to-Earnings			0.002	−0.001
			(0.004)	(0.001)
Constant	10.411*	0.404	9.537	2.921
	(5.395)	(2.132)	(6.785)	(2.960)
Observations	386	2,033	301	1,160
R^2	0.082	0.067	0.092	0.079
Adjusted R^2	0.052	0.061	0.048	0.067

Note: Standard error in parenthesis *p<0.1; **p<0.05; ***p<0.01

The first characteristic examined in Table 6 is the *company size*, where we use market capitalization as a proxy. The findings indicate a negative and significant relationship between *company size* and CAR for both sales and purchases, suggesting that CAR decreases as the *company size* increases. The model estimates that a 1 percent increase in *company size* leads to a 0.01055 percentage points decrease in CAR for insider sales, and a smaller decrease of 0.00518 percentage points for insider purchases. This is consistent with previous research by Aussenegg and Ranzi (2008), who argue that insider trades in small firms tend to have more pricing information than those in large firms, likely due to larger companies being more efficient and providing more information to the public.[19]

We also find that stocks with high volume relative to outstanding shares (high *turnover*) experience higher CAARs after insider purchases, while there is no significantly different response to sales. Our model indicates that an increase in turnover of 1 percent is associated with an increase in CAR by 0.00316 percentage points for purchases. This finding is consistent with our existing beliefs[20] and a recent study by Chang and Fang (2020), which reported a positive correlation coefficient of 0.8254 percent between abnormal returns and turnover.

Our cross-sectional analysis indicates that firms less vulnerable to bankruptcy (higher *Altman Z-scores*) do not yield statistically significant results for either sales or purchases. Conversely, companies with a higher proportion of intangible assets[21] relative to their market capitalization, demonstrate an increase of 0.03489 percentage points in CAR with a 1 percent increase in this ratio. This finding aligns with the results of Aboody and Lev (2000), who found a positive relationship between R&D and returns.[22]

Furthermore, we find that trades with larger transaction sizes relative to the market capitalization (high *Transaction Size ratio*) exhibit positive coefficients for purchases and negative coefficients for sales. We anticipate that larger transactions will convey more information and hence elicit stronger market reactions. However, the coefficients have a relatively modest magnitude, with the coefficient for sales being -0.00379 percentage points and the coefficient for purchases being 0.00422 percentage points.

[19] Ausenegg and Ranzi (2008) found that insider purchases in large companies are preceded by CAARs of -2.09 percent in 20 trading days before the transaction, and CARS of 0.04 percent in the 20 trading days after.
[20] In Chapter 5.2.1 we argued that we expect companies with higher turnover (increased numbers of shares traded) will demonstrate a higher abnormal return compared to companies with lower turnover.
[21] Goodwill is excluded from this characteristic. Refer to discussion in Chapter 5.2.1.2.
[22] Aboody and Lev (2000) found that firms with R&D activities exhibited a coefficient of 0.40 percent for insider purchases when examining the cumulative raw return in the event window [0, 1].

A higher number of *insiders owning shares* is associated with a positive coefficient for CAR of 0.082 percentage points. Outsiders can perceive the growing number of insiders as a strong signal to invest in the company's stocks, as insider purchases indicate a higher level of confidence in the company among insiders themselves. Conversely, stocks with a higher proportion of outstanding shares held by insiders (high *Insider Ownership ratio*) exhibit statistically significant coefficients for both sales and purchases, with negative coefficients of 0.0096 percentage points and 0.006 percentage points, respectively. This finding suggests that a higher ownership ratio among insiders can be perceived as a negative factor regarding outsiders' influence on the company. As voting rights increase among insiders, outsiders may have limited power to control the firm.

We observe a significant positive relationship between stock volatility and CAR for insider purchases, indicating that a 1 percent increase in *30-Day Volatility* corresponds to an estimated 0.00859 percentage point increase in CAR. This finding can be attributed to the higher number of investment opportunities created by high volatility, allowing investors to capitalize on fluctuations in stock prices over time.

Regarding characteristics related to valuation and performance, we find that companies with higher market expectations for future growth (high *price-to-book* ratio) do not exhibit statistically significant coefficients. Moreover, our findings indicate that stocks with a higher return on equity have a marginal, yet statistically significant, impact on CAR, with a positive effect from insider purchases and a negative effect from insider sales. These findings contradict our expectations regarding insider purchases. An insider purchase in a company with a strong valuation or performance is generally viewed positively as it confirms market beliefs but may elicit a weaker market reaction due to the lack of new information, and hence we expect a negative coefficient. The results indicate a positive increase of 0.01 percentage points with a 1 unit increase in the return on equity for insider purchases. The coefficient for insider sales in firms with higher valuations or stronger performance may provide more unfavorable information than for firms with lower valuations or weaker performances, leading to a negative coefficient. According to our expectations, this is yielding a change in CAR of -0.033 for one unit change in return on equity. Regarding the firms' revenue growth, our finding is as expected, as insider purchases exhibit a negative coefficient of 0.002 percent. However, this coefficient is marginal and thereby has little economic importance.

Finally, our analysis demonstrates a negative relationship between the *enterprise multiple* and CAR for purchases, confirming our initial beliefs for characteristics related to valuation and performance. Additionally, we find no statistically significant coefficients for *price-to-earnings*, suggesting that these findings may not have significant economic implications for our study.

Hypothesis V states that *the magnitude and direction of abnormal returns associated with insider trading are influenced by certain event and firm characteristics*. This observation only holds partially true for some of the characteristics, as we find several coefficients that are not statistically significant and of marginal magnitude.

7 Robustness Test

Robustness testing is a crucial method for assessing the reliability and validity of statistical findings, particularly in the presence of potential biases or limitations in the data or methods used. In addition to using multiple event windows in our cross-sectional regression analysis of the CAAR[23], we will conduct tests on heteroskedasticity and multicollinearity.

7.1 Heteroskedasticity Test for Cross-Sectional Analysis

A common method for detecting heteroskedasticity in a regression analysis is to perform a Breusch-Pagan test. The test was designed by Breusch T. S. and Pagan A. R. (1979) and is a commonly used method to formally test the presence of heteroskedasticity. The Breusch-Pagan test is based on the fundamental concept that heteroscedasticity in a regression model can be identified by the residuals of the model displaying varying levels of variance across different values of the characteristics (Breusch & Pagan, 1979). To evaluate the results, the p-value can be examined. If it is less than 0.05, we can reject the null hypothesis at a 5 percent significance level, meaning there is no heteroskedasticity in the regression. The Breusch-Pagan test was conducted for the cross-sectional regression presented in Table 6 for the main event window [0,1], with CAR as the dependent variable.

Table 7: Breusch-Pagan Test

The table shows the results from the Breusch-Pagan test for all four models used in the cross-sectional regression analysis in Table 6.

	(1: Sale)	(2: Purchase)	(3: Sale)	(4: Purchase)
BP	82.448	62.116	51.972	111.102
P-value	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)

Note: P-values in parenthesis. All values are below 0.0001.

[23] Refer to Table 11, 12, and 13 in Appendix C for cross-sectional regression with event window [0, 2], [-1, 1], and [-2, 2].

The p-values for all four regression models are less than 0.0001. This indicates that we can reject the null hypothesis, and hence, there is no evidence of heteroskedasticity in the regression.

7.2 Multicollinearity Test for Cross-Sectional Analysis

According to Wooldridge (2019), a high correlation between independent variables may lead to multicollinearity, and assessing multicollinearity is essential to the analysis. Multicollinearity can be measured using the Variance Inflation Factor (VIF), which provides a point of validation in the analysis. Investopedia (2023) suggests that if the VIF values are larger than 5, there may be issues estimating accurate coefficients in the model. In this study, we will measure the presence of multicollinearity among all the characteristics using these scales.

Table 8: Variance Inflation Factor (VIF)

The table shows the results from the Variance Inflation Factor (VIF) test for all characteristics used in the cross-sectional analysis in Table 6. The table contains four models represented by columns (1) through (4). Columns (1) and (2) present a cross-sectional analysis with observations on sales and purchases, respectively, excluding the characteristics Enterprise Multiple and PE. Columns (3) and (4) present a cross-sectional analysis with observations on sales and purchases, respectively, including the characteristics Enterprise Multiple and PE.

	(1: Sale)	(2: Purchase)	(3: Sale)	(4: Purchase)
Company Size	2.998	3.786	2.906	2.648
Turnover	1.654	1.573	1.307	1.416
Intangible Assets	1.078	1.102	1.037	1.021
Altman's Z-score	1.557	1.810	1.650	1.307
Transaction Size ratio	2.143	2.606	1.755	1.721
Number of Insiders Owning Shares	1.654	1.769	1.555	1.551
Insider Ownership ratio	1.473	1.605	1.527	1.465
30-Day Volatility	1.890	1.992	1.642	1.594
Price-to-Book	1.422	1.428	1.793	1.385
Return on Equity	1.702	2.248	1.435	1.207
Revenue Growth	1.096	1.150	1.133	1.038
Enterprise Multiple			1.395	1.100
Price-to-Earnings			1.141	1.070

Table 8 displays the summary of the VIF test. Notably, none of the coefficients exceed 5, with the majority ranging from 1 to 2. However, it is worth noting that *company size* and *transaction size* ratio exhibit slightly elevated values compared to the other characteristics. This suggests potential multicollinearity concerns, especially for *company size* in model (2). Nevertheless, following conventional practice, given the absence of coefficients exceeding 5 and the prevalence of coefficients within the 1 to 2 range, we can reasonably assume that multicollinearity is not a significant issue in the models.

8 Limitations

When interpreting the results, it is important to remember that the study has some limitations. Firstly, the study relied on manually registered notifications to identify insider trading activities. Although this is a frequently employed method, it is vulnerable to errors that could compromise the precision of the data. The dataset utilized in the study is subject to human errors both when companies report insider trades and when we extract the data. Despite efforts to correct errors, it is challenging to validate all the data due to the high volume of manually registered notifications. Furthermore, some insider trades may go unreported or missed during data extraction from NewsWeb, leading to omitted data. According to Kang (2013), missing data can reduce statistical power in a study and create biased estimates, leading to invalid conclusions.

Secondly, the event period in which insider trading activities were examined may have been influenced by other external factors, such as macroeconomic factors and similar announcements. Some insider trades might have been anticipated, which can lead to a bias of the measured effect in the event itself as the trade is already reflected in the stock price before our event window. Although we accounted for multiple trades in the same company on the same day, it is possible that the effect measured in the event window was affected by other events occurring during the same period.

Thirdly, one potential concern when using the event study methodology is the nonsynchronous trading effect, as noted by MacKinlay (1997). Since our analysis relies on the adjusted closing price, which is only recorded once per trading day, we assume that stock prices are measured at 24-hour intervals. However, the closing price is only represented by the last trade for the stock during the day, which can introduce bias into the beta of the market model. This assumption may not hold for actively traded securities, according to MacKinlay (1997), and may not be a significant issue in those cases.

Lastly, the sample size for insider sales is relatively small in some of the categories in the analysis. While the reason for this has been explained in Chapter 4.4, caution should be exercised when extending the implications of these findings to broader contexts or making significant decisions solely based on this limited sample.

9 Conclusion

This thesis contributes to the existing literature by studying insider trading and its impact on the stock prices on the Oslo Stock Exchange. Specifically, the study examines different transaction sizes, positions within companies, and industries involved. Additionally, we hypothesized that market reactions are influenced by specific firm and event characteristics.

Consistent with prior studies examining foreign stock markets, our findings suggest that insider purchases on the Oslo Stock Exchange generate abnormal returns. This provides evidence of the presence of asymmetric information between insiders and outsiders within the company, and also argues against the strong-form market efficiency on the stock market.

Our findings suggest that abnormal returns are influenced by transaction sizes in the case of insider purchases, as larger insider purchases convey stronger signals than smaller purchases. However, we cannot draw the same conclusion for sales. Additionally, our findings reveal that insider transactions made by individuals holding higher positions within the company positively influence abnormal returns. This suggests that outsiders perceive insiders in prominent positions to possess more valuable information regarding the company's operations and prospects. This effect is observed only for insider purchases, as we argue that the sale of shares by individuals holding prominent positions in the company is driven by motives other than profit, such as rebalancing portfolios and liquidity concerns.

In the final part of the event study, we observe abnormal returns from insider purchases in companies with a substantial proportion of R&D. This signifies the presence of significant uncertainty in R&D-intensive firms, and insider purchases act as positive signals to the market. However, the impact of insider trading is again only limited to purchases. Moreover, the analysis of specific event and firm characteristics yields mixed results, adding ambiguity to the influence on abnormal returns.

9.1 Further Research

Further research could extend our study by exploring alternative event and estimation windows to verify whether the results differ. Our analysis mainly used short event windows, and a 120-day estimation window which ends ten days before the event date. Therefore, it would be interesting to investigate longer event windows and shorter or longer estimation windows to examine the potential impact on market reactions to insider trading. Additionally, investigating the effects of the COVID-19 period exclusively may provide further insight into market reactions to insider trading during times of market turbulence.

Based on our findings, it appears that insider purchases generate larger abnormal returns compared to insider sales. A potential area for future research could be to use these findings to develop a trading strategy and examine its profitability. A similar approach was taken by Eckbo & Smith (1998), who investigated the long-term profitability of insider trading on the Oslo Euronext Growth and Oslo Stock Exchange by constructing a portfolio that follows purchases and sales and comparing its performance to a benchmark index. Another possibility could be to develop a trading strategy that utilizes insider purchase information on the Oslo Stock Exchange, and evaluate its viability through backtesting in the same period as our study.

An additional suggestion for further research would be to explore insider trading in other stock markets beyond the Oslo Stock Exchange. Specifically, investigating insider trading on Oslo Euronext's growth market could provide interesting insights, although limited data may pose a challenge. Furthermore, exploring insider trading in foreign markets and comparing the results to those obtained in our study could reveal potential differences due to varying legal frameworks or other factors worth further investigation.

Furthermore, looking at insider trading activity, specifically abnormal return, and volume, could be interesting during events such as acquisition announcements, earning announcements, and seasoned equity offerings. By identifying potential anomalies in the market, this type of research could pave the way for developing new trading strategies and contribute to a deeper understanding of the financial markets.

References

Aboody, D., & Lev, B. (2000). Information Asymmetry, R&D, and Insider Gains. The *Journal of Finance*, 55(6), 2747-2766.

Akerlof, G. A. (1970). The Market for «Lemons»: Quality Uncertainty and the Market Mechanism. *The Quarterly Journal of Economics*, *84*(3), 488-500.

Altman, E. I. (1968). FINANCIAL RATIOS, DISCRIMINANT ANALYSIS AND THE PREDICTION OF CORPORATE BANKRUPTCY. *The Journal of Finance*, *23*(4), 589–609.

Aussenegg, W., & Ranzi, R. (2008). Corporate Insider Trading and the Short-Run Price Impact of Private Information in Continental Europe. *Working paper*.

Barth, M. E., & Kasznik, R. (1999). Share repurchases and intangible assets. *Journal of Accounting and Economics*, 28(2), 211–241.

Beams, J. D. (2002). *Insider Trading: A Study of Motivations and Deterrents* [Doctoral dissertation]. Virginia Polytechnic Institute and State University.

Betzer, A., & Theissen, E. (2009). Insider Trading and Corporate Governance: The Case of Germany. *European Financial Management*, 15(2), 402–429.

Brealey, R. A., Myers, S. C., & Allen, F. (2017). *Principles of Corporate Finance*. McGraw-Hill Education.

Breusch, T. S., & Pagan, A. R. (1979). A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica*, 47(5), 1287-1294.

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1), 3–31.

Chae, J. (2005). Trading Volume, Information Asymmetry, and Timing Information. *The Journal of Finance*, 60(1), 413–442.

Chang, C. L., & Fang, M. (2020). Noise Trading and Abnormal Return in Stock Market. *Revista Argentina de Clínica Psicológica*, 29(4), 317–324.

Cheuk, M. Y., Fan, D. K., & So, R. W. (2006). Insider trading in Hong Kong: Some stylized facts. *Pacific-Basin Finance Journal*, 14(1), 73–90.

Chowdhury, M., Howe, J. S., & Lin, J.-C. (1993). The Relation between Aggregate Insider Transactions and Stock Market Returns. *The Journal of Financial and Quantitative Analysis*, 28(3), 431-437.

Coff, R. W., & Lee, P. M. (2002). Insider trading as a vehicle to appropriate rent from R&D. *Strategic Management Journal*, 24(2), 183–190.

Del Brio, E. B., Miguel, A., & Perote, J. (2002). An investigation of insider trading profits in the Spanish stock market. *The Quarterly Review of Economics and Finance*, 42(1), 73–94.

Ding, L., Lam, H. K. S., Cheng, T. C. E., & Zhou, H. (2018). A review of short-term event studies in operations and supply chain management. *International Journal of Production Economics*, 200, 329–342.

Eckbo, B. E., & Norli, Ø. (2005). Liquidity risk, leverage and long-run IPO returns. *Journal of Corporate Finance*, 11(1–2), 1–35.

Eckbo, B. E., & Smith, D. C. (1998). The Conditional Performance of Insider Trades. *The Journal of Finance*, 53(2), 467–498.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383-417.

Fama, E. F. (1995). Random Walks in Stock Market Prices. *Financial Analysts Journal*, 51(1), 75–80.

Fama, E. F. (1998). Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, 49(3), 283–306.

Fernando, J. (2022). Price-to-Book (PB) Ratio: Meaning, Formula, and Example. Retrieved March 10, 2023, from *Investopedia*. https://www.investopedia.com/terms/p/price-to-bookratio.asp

Fernando, J. (2023). Return on Equity (ROE) Calculation and What It Means. *Investopedia*. Retrieved March 10, 2023, from https://www.investopedia.com/terms/r/returnonequity.asp

Fidrmuc, J. P., Goergen, M., & Renneboog, L. (2006). Insider Trading, News Releases, and Ownership Concentration. *The Journal of Finance*, 61(6), 2931–2973.

Finanstilsynet. (2022a, November 12). *Forbud mot innsidehandel og tilskyndelse til innsidehandel*. Retrieved March 25, 2023, from https://www.finanstilsynet.no/tilsyn/markedsatferd/forbud-mot-innsidehandel-og-tilskyndelse-til-innsidehandel/

Finanstilsynet. (2022b, November 12). *Meldeplikt for personer med ledelsesansvar (primærinnsidere) og deres nærstående*. Retrieved March 25, 2023, from https://www.finanstilsynet.no/tilsyn/markedsatferd/meldeplikt-for-personer-med-ledelsesansvar/

Finnerty, J. E. (1976). INSIDERS AND MARKET EFFICIENCY. *The Journal of Finance*, 31(4), 1141–1148.

Firth, M., Leung, T. Y., & Rui, O. M. (2011). Insider Trading in Hong Kong: Tests of Stock Returns and Trading Frequency. *Review of Pacific Basin Financial Markets and Policies*, 14(03), 505–533.

Framstad, A. P. (2017, January 6). Stor E24-undersøkelse: Slik stiller selskapene seg til sjeldnere rapportering. *E24*. Retrieved March 25, 2023, from https://e24.no/boers-og-finans/i/G17m9V/stor-e24-undersoekelse-slik-stiller-selskapene-seg-til-sjeldnere-rapportering

Ganti, A. (2022). What Is Insider Trading, and When Is It Legal?. *Investopedia.* Retrieved February 20, 2023, from https://www.investopedia.com/terms/i/insidertrading.asp

Hayes, A. (2022a). Implied Volatility vs. Historical Volatility: What's the Difference?. *Investopedia.* Retrieved April 24, 2023, from https://www.investopedia.com/articles/investing-strategy/071616/implied-vs-historical-volatility-main-differences.asp

Hayes, A. (2022b). Enterprise Multiple (EV/EBITDA): Definition, Formula, Examples. *Investopedia*. Retrieved April 24, 2023, from https://www.investopedia.com/terms/e/ev-ebitda.asp

Huddart, S. J., & Ke, B. (2010). Information Asymmetry and Cross-sectional Variation in Insider Trading. *Contemporary Accounting Research*, 24(1), 195–232.

Investopedia. (2023). Variance Inflation Factor (VIF). Retrieved April 28, 2023, from https://www.investopedia.com/terms/v/variance-inflation-factor.asp

Jaffe, J. F. (1974). Special Information and Insider Trading. *The Journal of Business*, 47(3), 410–428.

Jeng, L. A., Metrick, A., & Zeckhauser, R. (2003). Estimating the Returns to Insider Trading: A Performance-Evaluation Perspective. *Review of Economics and Statistics*, 85(2), 453–471.

Kang, H. (2013). The prevention and handling of the missing data. *Korean Journal of Anesthesiology*, 64(5), 402.

Kendall, M. G., & Hill, A. B. (1953). The Analysis of Economic Time-Series-Part I: Prices. *Journal of the Royal Statistical Society. Series A (General)*, 116(1), 11-34.

Kenton, W. (2022a). What Are Intangible Assets? Examples and How to Value. *Investopedia*. Retrieved March 20, 2023, from https://www.investopedia.com/terms/i/intangibleasset.asp

Kenton, W. (2022b). Altman Z-Score: What It Is, Formula, How to Interpret Results. *Investopedia*. Retrieved April 24, 2023, from https://www.investopedia.com/terms/a/altman.asp

Kenton, W. (2022c). *Price-Earnings Relative*. *Investopedia*. Retrieved April 24, 2023, from https://www.investopedia.com/terms/p/price-earningsrelative.asp

Kothari, S. P., Laguerre, T. E., & Leone, A. J. (2002). Capitalization versus expensing: Evidence on the uncertainty of future earnings from capital expenditures versus R&D outlays. *Review of Accounting Studies*, 7(4), 355–382.

Laffont, J.-J., & Martimort, D. (2009). *The Theory of Incentives: The Principal-Agent Model*. Princeton University Press.

Lakonishok, J., & Lee, I. (2001). Are Insider Trades Informative? *Review of Financial Studies*, 14(1), 79–111.

Levine, R., Lin, C., & Wei, L. (2017). Insider Trading and Innovation. *The Journal of Law and Economics*, 60(4), 749–800.

Lorie, J. H., & Niederhoffer, V. (1968). Predictive and Statistical Properties of Insider Trading. *The Journal of Law and Economics*, 11(1), 35–53.

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

Manne, H. G. (1966). *Insider Trading And The Stock Market*. The Free Press.

McWilliams, A., & Siegel, D. (1997). Event Studies in Management Research: Theoretical and Empirical Issues. *Academy of Management Journal*, 40(3), 626–657.

Medleva, V. (2019). *Oslo Stock Exchange: a whole new world of opportunities*. Capital. Retrieved May 12, 2023, from https://capital.com/the-oslo-stock-exchange

Mishkin, F. E. (2003). *The Economics of Money, Banking and Financial Markets* (8. ed.). Addison-Wesley.

MSCI. (n.d.). The Global Industry Classification Standard (GICS®). Retrieved March 23, 2023, from https://www.msci.com/our-solutions/indexes/gics

National Science board. (2020). *Production and Trade of Knowledge- and Technology-Intensive Industries*. Science and Engineering Indicators. Retrieved April 18, 2023, from https://ncses.nsf.gov/pubs/nsb20205/production-patterns-and-trends-of-knowledge-and-technology-intensive-industries

Norges Bank. (n.d.). Valutakurser. Retrieved March 14, 2023 from https://www.norges-bank.no/tema/Statistikk/Valutakurser/

NOU 2016: 2. (2016). Endringer i verdipapirhandelloven – flagging og periodisk rapportering— Gjennomføring av endringer i rapporteringsdirektivet. Finansdepartementet.

Oslo Børs (2022). Norwegian Air Shuttle ASA (NAS) - Mandatory notification of trade. NewsWeb. Retrieved March 22, 2023, from https://newsweb.oslobors.no/message/579302

Oxford University Press. (n.d.). Inside track. In Oxford English Dictionary. Retrieved May 12, 2023, from https://www.oed.com/view/Entry/96816?redirectedFrom=inside+track#eid347728

Palmer, B. (2021). What Does It Mean When a Company's P/E Ratio Reads «N/A»? *Investopedia*. Retrieved March 15, 2023, from https://www.investopedia.com/ask/answers/09/price-earnings-pe-not-applicable.asp

Ryu, D., Yang, H., & Yu, J. (2022). Insider trading and information asymmetry: Evidence from the Korea Exchange. *Emerging Markets Review*, 51, 100847.

Schotland, R. A. (1967). Unsafe at Any Price: A Reply to Manne, Insider Trading and the Stock Market. *Virginia Law Review*, 53(7), 1425.

Seyhun, H. N. (1986). Insiders' profits, costs of trading, and market efficiency. *Journal of Financial Economics*, 16(2), 189–212.

Seyhun, H. N. (1998). *Investment intelligence from insider trading*. The MIT Press.

Tronstad, L. (2022, January 6). Robert Næss mener en rekke selskaper er uvanlig høyt priset i 2022 – én sektor skiller seg ekstra ut. *Dagens Næringsliv*. Retrieved April 10, 2023, from https://www.dn.no/bors/finans/oslo-bors/aksjer/robert-nass-mener-en-rekke-selskaper-er-uvanlig-hoyt-priset-i-2022-en-sektor-skiller-seg-ekstra-ut/2-1-1140279

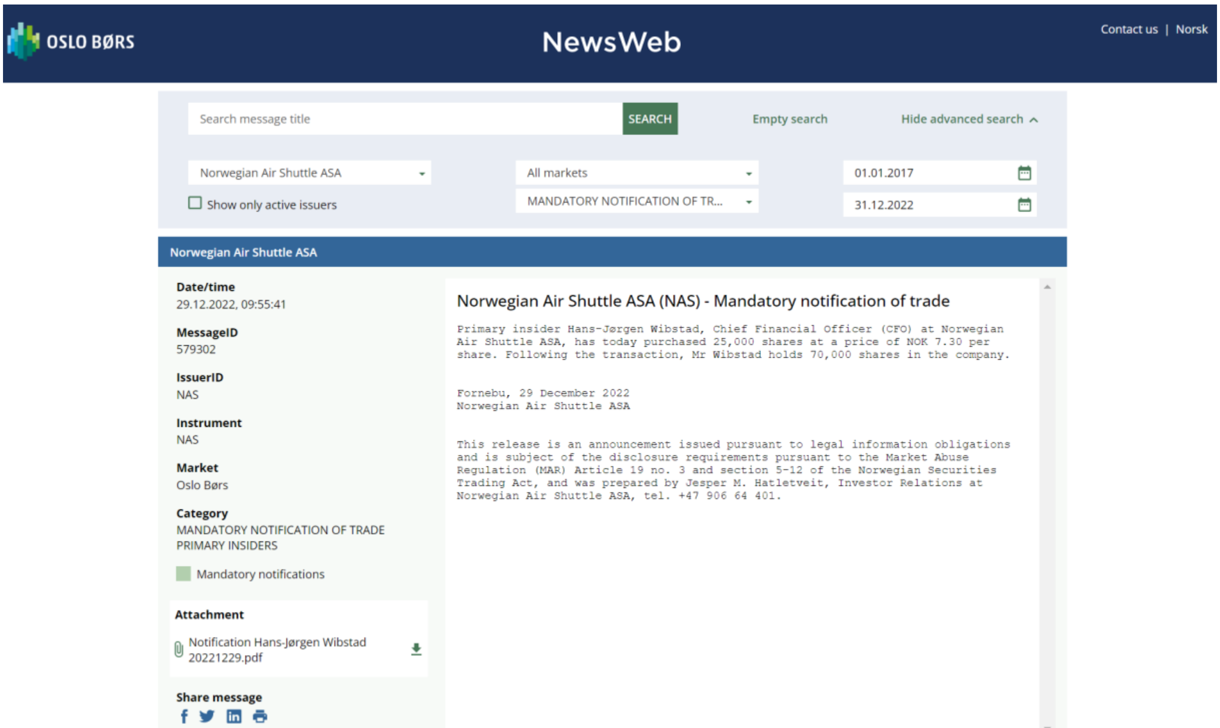
Verdipapirhandelloven. (2017). *Lov om verdipapirhandel* (LOV-2007-06-29-75). Lovdata. Retrieved March 14, 2023, from https://lovdata.no/dokument/NL/lov/2019-06-21-65

Wooldridge, J. M. (2019). *Introductory Econometrics: A Modern Approach* (7. ed.). South-Western College.

Appendix

A Miscellaneous Material and Data

A.1 Notification on NewsWeb



The presented excerpt features an arbitrary insider trade notification retrieved from NewsWeb (Oslo Børs, 2022). Notably, the selected timeframe for analysis is from 01.01.2017 to 31.12.2022, specifically focusing on insider trading notifications ("MANDATORY NOTIFICATION OF TRADE PRIMARY INSIDERS") registered exclusively on the Oslo Stock Exchange. This excerpt highlights an insider trade executed by the Chief Financial Officer of Norwegian Air Shuttle ASA within the company. The notification above will serve as a source for extracting several variables of interest, including the ticker name (NAS), company name (Norwegian Air Shuttle ASA), the insider's position within the company (CFO), the transaction type (Purchase), date of the transaction (29.12.2022), transaction volume (25,000), transaction price (7.3), and currency used for the transaction (NOK). A systematic information retrieval process was conducted for all transactions within the selected timeframe that meet the selection objectives, as described in Chapter 4.1.

A.2 Regression Between Net Purchase Ratio and Average Age of Companies

Table 9: Regression Between Net Purchase Ratio and Average Age of Companies

This table presents the results from the regression between the net purchase ratio and the average age of the companies listed on the Oslo Stock Exchange (explanatory variable). The average age of the companies is measured as the average number of years from the insider trade to the listing date for each company. The net purchase ratio is measured as purchases less sales, divided by the total number of insider trades within the company. It presents the coefficient, standard error, t-stat, p-value, median, mean, and number of observations (N).

	Coefficient	Standard Error	T-stat	P-value	Median	Mean	N
Net purchase ratio					0.9	0.7	207
Average age of companies	0.0018	0.0019	0.9343	0.3512	11	14	207

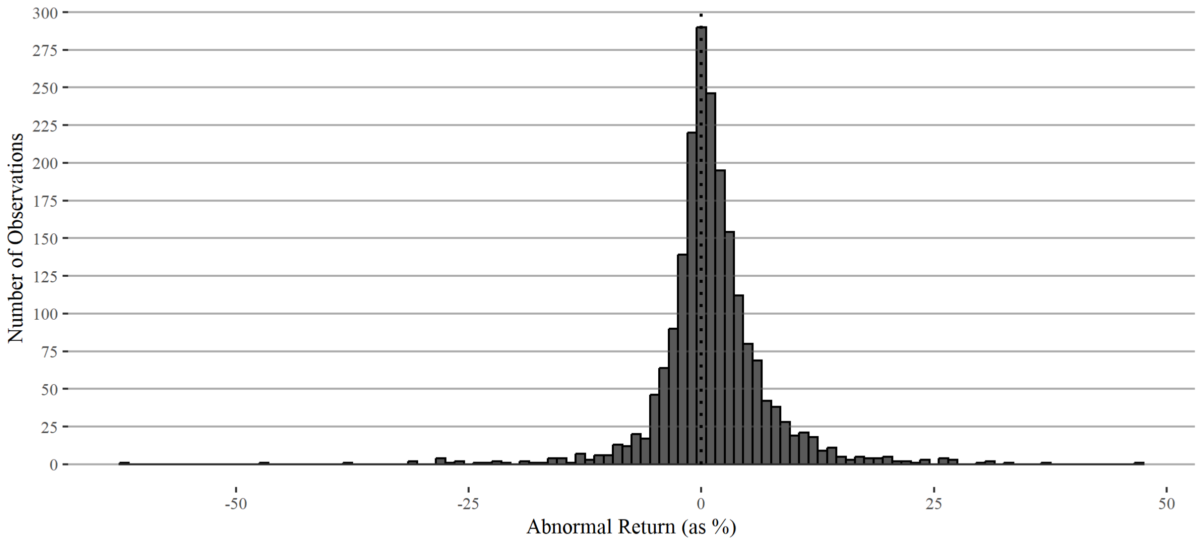
The relationship between those two variables was examined to test whether the company age of the listed companies on the Oslo Stock Exchange caused the large difference in the number of insider purchases and sales. There is no significant correlation between the two variables, as evidenced by the p-value of 35 percent. This indicates that the large difference in the number of insider purchases and sales is not caused by the age of the companies listed on the Oslo Stock Exchange.

B Event Study

B.1 Histogram of CAR for Insider Purchases

Figure 5: Histogram of CAR for All Insider Purchases in the Event Window [0, 1]

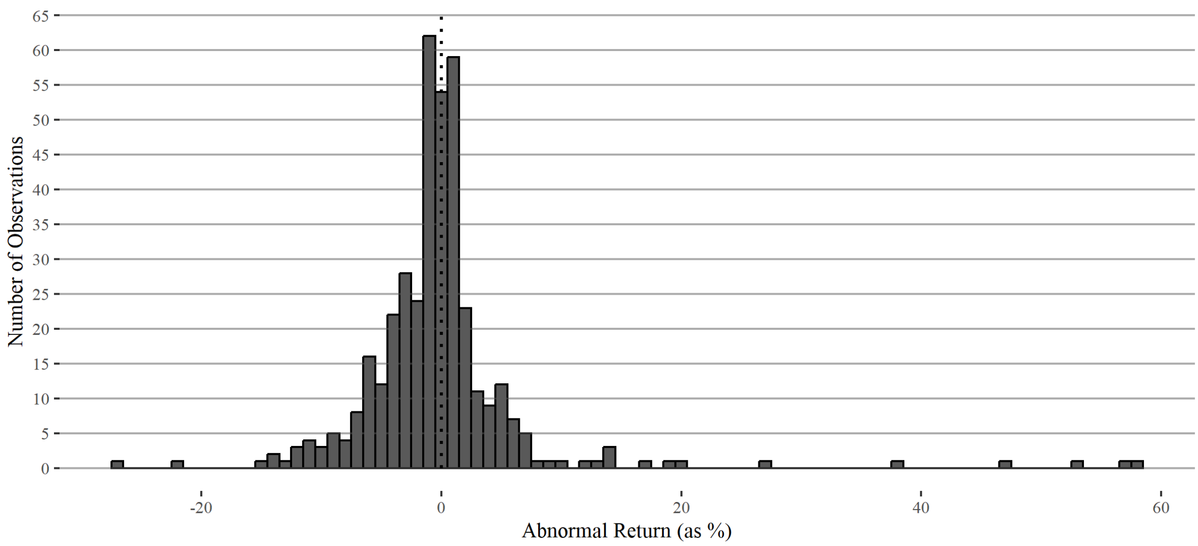
This figure shows the distribution of CAR for all insider purchases above NOK 100,000 during the main event window [0, 1].



B.2 Histogram of CAR for Insider Sales

Figure 6: Histogram of CAR for All Insider Sales in the Event Window [0, 1]

This figure shows the distribution of CAR for all insider sales above NOK 100,000 during the main event window [0, 1].



B.3 Unrelated Simultaneous Events

Table 10: Simultaneous Events Affecting CAAR for Small Sales

Company	**Date of insider trade**	**Daily abnormal return in the event window [-2, 2], where day [0] is the day of the announcement.**	**Reason and [event day affected]**	**Source of announcement**
KMC Propoterties ASA	15.12.2020	[-2]: 24% [-1]: 16% [0]: -1% [1]: 58% [2]: -15%	Announcement on successful completion of private placement on day [-2] and [-1]. Change of company name and strategy on day [1].	**Private placement:** https://newsweb.oslobors.no/message/520446 **Change of company name:** https://newsweb.oslobors.no/message/520814
KMC Propoterties ASA	29.05.2020	[-2]: 1% [-1]: 86% [0]: 14% [1]: 1% [2]: 8%	Announcement on a new stand-still agreement (refinancing of loans), affects day [-1].	**Stand-still agreement:** https://newsweb.oslobors.no/message/506634
Interoil Exploration and Prod. ASA	07.09.2017	[-2]: -2% [-1]: 1% [0]: 1% [1]: 37% [2]: 22%	Announcement on the purchase of a Gas Plant on day [1].	**Gas plant:** https://newsweb.oslobors.no/message/434357
Schibsetd ASA	03.11.2017	[-2]: 0% [-1]: 2% [0]: 18% [1]: -1% [2]: -3%	Announcement on strong Q3 results on day [0].	**Release of Q3-report:** https://newsweb.oslobors.no/message/437862
XXL ASA	18.05.2020	[-2]: 8% [-1]: -6% [0]: 14% [1]: 14% [2]: -4%	Announcement related to private placement on day [1].	**Private placement:** https://newsweb.oslobors.no/message/506012

C Cross-Sectional Regression Models

C.1 Cross-Sectional Regression with Event Window [0, 2]

Table 11: Cross-Sectional Regression with Event Window [0, 2]

The table contains four models represented by columns (1) through (4). Columns (1) and (2) present a cross-sectional analysis with observations on sales and purchases, respectively, excluding the characteristics Enterprise Multiple and PE. Columns (3) and (4) present a cross-sectional analysis with observations on sales and purchases, respectively, including the characteristics Enterprise Multiple and Price-to-Earnings. The event period is set to the announcement day and two days after.

	Dependent variable:			
	CAR [0, 2]			
	(1: Sale)	(2: Purchase)	(3: Sale)	(4: Purchase)
ln(Company Size)	−1.325**	−0.724***	−0.855	−0.676***
	(0.570)	(0.191)	(0.648)	(0.232)
ln(Turnover)	−0.933	0.348*	−0.739	−0.361
	(0.624)	(0.200)	(0.644)	(0.233)
ln(Intangible Assets)	3.232	5.858**	9.266	3.533
	(14.290)	(2.758)	(13.233)	(3.008)
ln(Altman's Z-score)	0.228	0.104	0.662	0.214
	(0.919)	(0.195)	(1.121)	(0.409)
ln(Transaction Size ratio)	−0.766**	0.589***	−0.938**	0.525***
	(0.361)	(0.123)	(0.387)	(0.145)
Number of Insiders Owning Shares	−0.046	0.144***	−0.054	0.095*
	(0.142)	(0.040)	(0.149)	(0.049)
log(Insider Ownership ratio)	−1.660**	−1.208***	−0.003	−1.515***
	(0.832)	(0.284)	(0.922)	(0.378)
log(30-Day Volatility)	−0.343	1.720***	−2.210	1.435**
	(1.348)	(0.465)	(1.497)	(0.619)
ln(Price-to-Book)	−0.250	−0.125	0.089	−0.146
	(0.949)	(0.357)	(0.997)	(0.504)
Return on Equity	−0.028	0.005	−0.051	−0.002
	(0.030)	(0.007)	(0.032)	(0.011)
Revenue Growth	−0.009	−0.003*	0.009	−0.003
	(0.012)	(0.001)	(0.013)	(0.002)
Enterprise Multiple			−0.040	−0.027***
			(0.050)	(0.008)
Price-to-Earnings			0.007	−0.002
			(0.006)	(0.001)
Constant	17.272*	−1.508	18.473*	0.636
	(8.908)	(3.045)	(10.547)	(4.020)
Observations	386	2,033	301	1,160
R^2	0.048	0.157	0.060	0.177
Adjusted R^2	0.016	0.151	0.012	0.166

Note: Standard error in parenthesis **p<0.1; **p<0.05; ***p<0.01*

C.2 Cross-Sectional Regression with Event Window [-1, 1]

Table 12: Cross-sectional Regression with Event Window [-1, 1]

The table contains four different models represented by columns (1) through (4). Columns (1) and (2) present a cross-sectional analysis with observations on sales and purchases, respectively, excluding the characteristics Enterprise Multiple and PE. Columns (3) and (4) present a cross-sectional analysis with observations on sales and purchases, respectively, including the characteristics Enterprise Multiple and Price-to-Earnings. The event period is set to one day before and after the announcement day.

	Dependent variable:			
	CAR [-1, 1]			
	(1: Sale)	(2: Purchase)	(3: Sale)	(4: Purchase)
ln(Company Size)	−1.185**	−0.578***	−0.657	−0.565***
	(0.462)	(0.165)	(0.481)	(0.202)
ln(Turnover)	−0.599	0.199	−0.361	0.348*
	(0.506)	(0.172)	(0.478)	(0.202)
ln(Intangible Assets)	1.398	6.471***	7.464	2.593
	(11.582)	(2.377)	(9.821)	(2.611)
ln(Altman's Z-score)	0.749	0.110	1.248	0.449
	(0.745)	(0.168)	(0.832)	(0.355)
ln(Transaction Size ratio)	−0.569*	0.579***	−0.763***	0.518***
	(0.293)	(0.106)	(0.288)	(0.126)
Number of Insiders Owning Shares	0.013	0.111***	0.013	0.070
	(0.115)	(0.035)	(0.110)	(0.043)
ln(Insider Ownership ratio)	−1.543**	−0.983***	0.122	−1.282***
	(0.674)	(0.244)	(0.684)	(0.328)
log(30-Day Volatility)	0.051	1.217***	−0.998	0.857
	(1.093)	(0.401)	(1.111)	(0.537)
ln(Price-to-Book)	−1.060	−0.369	−0.920	−0.248
	(0.769)	(0.309)	(0.740)	(0.437)
Return on Equity	−0.014	0.011**	−0.031	−0.001
	(0.024)	(0.006)	(0.024)	(0.009)
Revenue Growth	−0.014	−0.002*	−0.001	−0.002
	(0.010)	(0.001)	(0.010)	(0.001)
Enterprise Multiple			−0.014	−0.025***
			(0.037)	(0.007)
Price-to-Earnings			0.006	−0.001
			(0.005)	(0.001)
Constant	13.954*	−0.931	11.685	1.536
	(7.220)	(2.625)	(7.828)	(3.489)
Observations	386	2,033	301	1,160
R^2	0.055	0.102	0.064	0.116
Adjusted R^2	0.022	0.097	0.016	0.105

Note: Standard error in parenthesis *p<0.1; **p<0.05; ***p<0.01

C.3 Cross-Sectional Regression with Event Window [-2, 2]

Table 13: Cross-sectional Regression with Event Window [-2, 2]

The table contains four models represented by columns (1) through (4). Columns (1) and (2) present a cross-sectional analysis with observations on sales and purchases, respectively, excluding the characteristics Enterprise Multiple and PE. Columns (3) and (4) present a cross-sectional analysis with observations on sales and purchases, respectively, including the characteristics Enterprise Multiple and Price-to-Earnings. The event period is set to two days before and after the announcement day.

	Dependent variable:			
	CAR [-2, 2]			
	(1: Sale)	(2: Purchase)	(3: Sale)	(4: Purchase)
ln(Company Size)	-1.118^{***}	-0.699^{***}	-1.041^{**}	-0.724^{***}
	(0.365)	(0.153)	(0.467)	(0.188)
ln(Turnover)	−0.385	0.367^{**}	−0.315	-0.316^{*}
	(0.397)	(0.159)	(0.461)	(0.188)
ln(Intangible Assets)	−3.946	4.467^{***}	1.084	3.542^{**}
	(6.193)	(1.1371)	(6.706)	(1.561)
ln(Altman's Z-score)	−0.294	0.112	0.225	0.375
	(0.589)	(0.155)	(0.806)	(0.331)
ln(Transaction Size ratio)	-0.536^{**}	0.454^{***}	-0.707^{***}	0.413^{***}
	(0.232)	(0.097)	(0.279)	(0.117)
Number of Insiders Owning Shares	0.103	0.115^{***}	1.134	0.086^{**}
	(0.091)	(0.032)	(0.106)	(0.040)
ln(Insider Ownership ratio)	-1.161^{**}	-0.922^{***}	−0.397	-1.050^{***}
	(0.533)	(0.227)	(0.663)	(0.305)
log(30-Day Volatility)	0.959	1.143^{***}	0.430	0.552
	(0.863)	(0.372)	(1.073)	(0.501)
ln(Price-to-Book)	0.503	−0.102	0.612	0.025
	(0.607)	(0.287)	(0.709)	(0.407)
Return on Equity	-0.034^{*}	0.013^{**}	-0.053^{***}	0.003
	(0.019)	(0.005)	(0.023)	(0.009)
Revenue Growth	−0.004	-0.002^{**}	0.001	-0.003^{*}
	(0.008)	(0.001)	(0.010)	(0.001)
Enterprise Multiple			−0.021	-0.017^{***}
			(0.036)	(0.007)
Price-to-Earnings			0.002	−0.001
			(0.005)	(0.001)
Constant	8.679	0.671	9.311	3.436
	(5.696)	(2.438)	(7.528)	(3.254)
Observations	386	2,033	301	1,160
R^2	0.124	0.072	0.140	0.077
Adjusted R^2	0.096	0.067	0.0990	0.066
Note: Standard error in parenthesis				**p<0.1; **p<0.05; ***p<0.01*