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Market Reactions to Legal Insider Trading on Oslo Stock Exchange Marketplaces

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Abstract

This paper investigates market reactions to legal insider trades on the Oslo Stock Exchange and analyses whether being listed on the sub-marketplace Merkur Market causes abnormal returns and turnover from insider transactions. Merkur Market is an alternative marketplace with more lax regulations, which we speculate causes a higher degree of information asymmetry between corporate insiders and outside investors. This could further yield excess market reactions. There are several major findings from our study. Firstly, insider purchases on the Oslo Stock Exchange cause both short-term abnormal return and turnover. Secondly, reactions from insider sales are weaker than from insider purchases. We argue that this may be due to insiders often selling for liquidation or diversification purposes. Thirdly, we find that both abnormal return and abnormal turnover from insider purchases are significantly higher for companies listed on Merkur Market than for those listed on the main exchange (XOSL). Finally, we compare market reactions from Merkur Market companies to a matched XOSL sample and find that being listed on Merkur Market cause abnormal returns of 5.60 per cent and an increase in turnover of 3.76 per cent for insider purchases.

Keywords – Legal insider trading, information asymmetry, Oslo Stock Exchange

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1 Introduction

Corporate insiders often possess superior information to outside investors and their trading activity consequently provides useful guidance about the underlying value of the company. Researchers have previously documented that the information content of insider trades causes market reactions, and further that the reactions increase in line with information asymmetry.[1] However, does the sub-marketplace companies are listed on effect market reactions from insider trades?

During the last few years there has been an emergence of alternative marketplaces aiming to enable small-cap growth companies to access capital markets, with Merkur Market[2] (MERK) being the equivalent on the Oslo Stock Exchange. MERK offers both less regulatory requirements and a much less extensive listing process than the main exchange (XOSL).[3] Listings on MERK are increasing in popularity, with 47 companies listed in 2020 alone against five listings on XOSL (Slettedal, 2020). The marketplace is also increasing in popularity amongst both institutional and retail investors. However, we hypothesise that the lax regulations this marketplace imposes, has implications for information asymmetry between the corporate insiders and outside investors.

Given the evidence of increased market reactions in information asymmetry, this thesis investigates whether being listed on MERK has implications for market reactions from insider trading. We find an effect of 5.60 per cent higher abnormal return and a 3.76 per cent increase in abnormal turnover around insider trades from being listed on MERK. The economically and statistically significant deviations in market reactions from insider trades caused by choice of listing venue on the same stock exchange, implies that there exists an internal imbalance of information content. The Oslo Stock Exchange has expressed the importance of Merkur Market being perceived as an efficient marketplace with sufficient transparency, to which we find contradicting evidence (Oslo Stock Exchange, 2015). These findings should therefore be of particular interest to policy researchers and regulatory authorities concerned with market efficiency and the consequences of

[1] Aboody and Lev (2000) show that R&D intensive firms have greater price reactions. Hong et al. (2000) provide evidence that momentum are larger for insiders in small firms and firms with low analyst coverage.

[2] Merkur Market changed name in October 2020 to *Oslo Euronext Growth*. Throughout this thesis, we will use the name *Merkur Market* (MERK).

[3] Comparable description of XOSL and MERK in Table 11 in the Appendix.

information asymmetry.

This thesis offers three major contributions to previous literature. Firstly, to the best of our knowledge there are no existing studies investigating the short-term market reactions from insider trades on the Oslo Stock Exchange. Eckbo and Smith (1998) investigated insider gains from portfolios mimicking Oslo Stock Exchange insiders' activities and found no evidence that insiders outperform the market. However, the regulations at the time precluded analysis of the short-term market reactions and therefore gives no implications as to the short-term effect of insider trades. For the aggregated sample, we find a cumulative average abnormal return (CAAR) from insider purchases of 1.74 per cent around the event date. This is higher than for both the US Stock Exchange with 0.59 per cent (Lakonishok & Lee, 2001) and the UK Stock Exchange with 1.16 per cent (Fidrmuc et al., 2006). This suggests that information content is higher for insider trades on the Oslo Stock Exchange.

Secondly, there is no existing literature that examines market reactions from insider trades and differentiate for sub-marketplaces on the same stock exchange. However, there are other studies that investigate the impact of information asymmetry. For example, Aboody and Lev (2000) who find a 0.20 per cent difference in abnormal returns for high versus low R&D firms ex-post insider trades and Chari et al. (1988) who finds that price reactions for small firms are 8.27 per cent higher than for large firms on the event date of earnings announcements. This compared to our findings of 5.60 per cent higher abnormal returns from insider trades as a result of being listed on MERK. Further, Chae (2005) finds information asymmetry to be positively correlated with abnormal turnover from information-generating events. Our results are in line with this finding, providing evidence of abnormal turnover increasing by 3.76 per cent if a company is listed on MERK rather than XOSL. Moreover, the methodology we use exceeds the traditional event study approach preformed by the former by using a cross-sectional regression model with a matched sample. This allows us to investigate any causal effects, whilst the former interpret the differences in coefficients.

Lastly, our findings are derived from an unparalleled dataset of insider transactions. The Oslo Stock Exchange announce insider trades as string text, and there is no available structured data to conduct quantitative analysis of the nature in this thesis. All insider trades from the sample period have been manually extracted, inspected and further categorised, leaving a unique data sample that is also applicable for further analysis on the topic.

Our analysis uses the event study methodology to extract cumulative average abnormal returns (CAAR) and cumulative average abnormal turnover (CAAV) for buy and sell activity across transaction value and marketplace categories.[4] Further, we preform a comparative analysis using a cross-sectional regression model with cumulative abnormal returns (CAR) and cumulative abnormal turnover (CAV) from the event study, as dependent variables.[5] First, we perform an analysis for the full sample, before we construct a comparable sample from XOSL using propensity score matching. The aim is to fulfill the requirements for causal inference between the Oslo Stock Exchange listing venue and market reactions to insider trades. The examined transactions are legal insider trades that have been reported to the Oslo Stock Exchange between 01.01.2017 and 28.02.2020 by insiders in companies exclusively listed on XOSL or MERK. This thesis only examines legal and publicly available insider trades. Thus, the findings give no indication to the effects of illegal insider trades, such as third-party trading, and insider trading refers only to legal insider trading in the further.

The remainder of this thesis is structured as follows. First, in Section 2, we perform a review of the theoretical framework and related literature on insider trading and asymmetric information, as well as a description of current regulations on insider trading. A description of the collection and treatment of the data, along with an explanation of the matching process is presented in Section 3. Furthermore, Section 4 introduces the event study methodology and the regression models used in the analysis, before our results are presented and discussed in Section 5. The limitations of the study are discussed in Section 6. Lastly, our findings are concluded in Section 7, where we also provide limitations and guidance for further research on the topic.

[4] CAAR is calculated using arithmetic returns and CAAV is calculated using logarithmic turnover. Overlapping events are aggregated into equally weighted portfolios.

[5] CAR is based on logarithmic abnormal returns with βs estimated from the market model with event window [-110, 20]. CAV is measured as logarithmic abnormal turnover (Daily volume/mCap). A transaction value cap of NOK (Norwegian krone) 125,000 apply for both models.

2 Literature review

This section defines insider trading and explains current regulations, before we address related theoretical and empirical literature on legal insider trading and information asymmetry. Theory on market efficiency and asymmetric information is presented before reviewing empirical evidence on insider gains, market reactions to insider trading and the implications of asymmetric information.

2.1 Insider trading and Oslo Stock Exchange regulations

Insider trading has been a widely debated topic in finance literature and involves the trading of public financial instruments by individuals who are closely related to the firm in question. Individuals classified as insiders include large shareholders, chief executive officers, top management and members of the Board of Directors. Such individuals will at times possess information that is expected to affect future cash-flows and ultimately the stock price of the company. Corporate insiders could exploit this information by buying stocks prior to an abnormal price increase, or by selling stocks before a price decline. Moreover, the activity of insiders could portray information that is not yet reflected in the current market price, which again could yield market reactions.

Whether insider trading should be subject to regulation is disputed. Critiques argue that insider trading can be considered an adequate entrepreneurial compensation for innovation of ideas that are not easily linked to profit (Manne, 1967). Furthermore, insider trading can increase market efficiency by conveying information to other market participants and thereby moving the market price closer to the fundamental value of the firm (Manne, 1992). For example, Leland (1992) found that stock prices are generally higher and convey more information when insiders trade actively. However, many argue that information asymmetry, where market participants have deviating material information concerning the underlying value of a security provides insiders with an unethical advantage, which can discourage outsider market activity (Ausubel, 1990). To control for the latter, the vast majority of countries with an active stock exchange have implemented laws and regulatory systems for insider trading activities in order to prevent insider gains at the expense of uninformed market participants (Bhattacharya & Daouk, 2002). In Norway, insider trading is legal and encouraged, with an exemption of trading on information that is likely to have a significant effect on the stock price of a company (Oslo Stock Exchange, 2020a). Furthermore, all primary insiders are obligated to report their trades to the Oslo Stock Exchange in accordance with the requirements set by the Norwegian Securities Trading Act. The deadline to notify an insider trade is no later than the start of trading the following day and the notified trades shall, according to the Securities Trading Act, be publicly disclosed directly, with certain exemptions (The Financial Supervisory Authority of Norway , 2019). The implication from this is that the lag from when an insider trade is executed until it is reported shall in theory be no longer than one day.

2.2 Market efficiency

The most central function of capital markets is allocation of financial assets, where market prices ideally should work as informed indicators for allocation of resources (Fama, 1998). In an efficient market, all available information is fully reflected in the price of financial assets. This indicates that it would not be possible for investors to profit from investment strategies. If insider trades cause reactions in stock prices, it would suggest that the transactions provide information that is not yet reflected in the market.

The infamous efficient market hypothesis was introduced by Fama in 1970 and claims that the price of a security reflects all available information about the asset. As new information emerges, investors revise their expectations and the price of the security will adjust thereafter. Overvaluation and undervaluation will be noncurrent as all market participants possess the same information. The model does not dismiss anomalies, but mispricing is said to be eliminated as overreactions and underreactions are equally common. According to the theory, outperforming the market is therefore unachievable.

The null hypothesis of the efficient market model is that all available information is at all times fully reflected in the market price. Fama (1970) recognises that this is an extreme hypothesis and introduces three forms of market efficiency to more easily test the degree of information at which the hypothesis does not hold. Weak form market efficiency claims that the only information reflected in security prices is historical data on the price movements or returns of a security. Most empirical evidence finds that markets are efficient in weak form, supporting the random walk model. Semi-strong market efficiency suggests that all obvious publicly available information is reflected in security prices. Semi-strong market tests investigate how prices adjust to events that generate price-sensitive information, typically public announcements. Strong form market efficiency assumes that all information is fully reflected in the price. Moreover, the requirements for both weak form and semi-strong form hold, and it is not possible to profit if an individual possesses monopolistic information.

Market reactions to insider trading tests strong form market efficiency. If insider transactions generate abnormal returns or abnormal trading volume, it would be inconsistent with the theory on efficient capital markets. The analysis in this thesis is restricted to strong form market efficiency. A semi-strong test using insider trades would test whether outsiders would be able to profit from the information of insider trades by constructing portfolios that mimic the behaviour of insiders. However, for the purpose of our analysis we only test strong-form market efficiency by concentrating on short-term market implications from insider trades.

2.3 Information asymmetry

If the efficient market hypothesis does not hold for insider trades, it suggests that corporate insiders are in possession of superior information that ultimately affects the value of the firm. It is reasonable to assume that asymmetric information is present for insiders, as management has continuous insight into productivity and operations, while outside investors only possess highly aggregated information provided at specific points in time. Asymmetric information conceptualises the information imbalance between two parties in a transaction and is thereby highly relevant when investigating insider gains.

George et al. (1970) first introduced the concept of information asymmetry in their paper *The Market for Lemons: Quality Uncertainty and the Market Mechanism.* They focus on the concept of Adverse Selection, which is the most relevant form of information asymmetry to insider trading. Adverse selection is the phenomenon of one party purposely withholding information before reaching an agreement, to maximise own gains. This is directly applicable to insider trading as insiders at times will possess information that is crucial to the future performance of the firm, and can choose to act on it. Insiders can use the information to their advantage through buying company stock in advance of positive announcements, or by selling stock in advance of announcements that are predicted to devalue the stock price. The theory suggests that a higher level of information asymmetry leads to an increased probability of mispricing. Applying this to the scenario of insider trading would suggest that market reactions will be larger for firms with a high degree of information asymmetry. On the back of this, we hypothesise that due to the characteristics of MERK as a marketplace, market reactions from information-generating events will be stronger.

2.4 Insider trading and profitability

There are several papers that examine the profitability of legal insider trading, where most research concludes that insiders tend to outperform the market. Lorie and Niederhoffer (1968) were pioneers in presenting evidence on the profitability of insiders by examining insider trading activity from 105 New York Stock Exchange companies. Their research concludes that when insiders excessively purchase a security, the security is expected to outperform the market for six months following the transaction. Further early research on the topic includes that of Jaffe (1974) and Rozeff and Zaman (1988) who found that corporate insiders achieve statistically significant abnormal returns post trading. Finnerty (1976) also found evidence that insiders are able to identify and profit from private material information, discarding the strong-form market efficiency hypothesis. Moreover, there seems to be strong evidence of insider gains where insider portfolios outperform the market with reported abnormal returns ranging from 3 per cent to 30 per cent (Lin & Howe, 1990; Seyhun, 1998; Jeng et al., 2003; Pratt & DeVere, 1970).

On the other hand, the conclusions on the profitability of mimicking portfolios are more ambiguous. Literature on this topic ultimately tests the semi-strong market efficiency hypothesis by examining whether outsiders can profit from the publicly available information from reported insider trades. Using the market model, Rozeff and Zaman (1988) conclude that outsiders can earn annual abnormal returns of 6 per cent through acting on publicly available information concerning insider trades. Whilst these results are in violation of the semi-strong market efficiency hypothesis, both Rozeff and Zaman (1988) and Jaffe (1974) found that when assuming a transaction cost of 2 per cent, the abnormal returns from mimicking insiders' activities disappear or turn negative. Furthermore, Seyhun (1986) provides evidence that the semi-strong market efficiency holds by concluding that the realisable return to outsiders is non-positive despite finding that insiders predict abnormal future share prices.

The research discussed above is conducted on foreign exchanges. Previous literature on insider trading on Oslo Stock Exchange is limited, with the exception of a study by Eckbo and Smith (1998). They examined the performance of insider portfolios, tracking the movements of insiders' buy and sell activity. The methodology they use is a conditional portfolio benchmark approach that constructs and aggregates replicating portfolios of insiders' actual trading behaviour and compare them to the performance of active mutual funds. The study rejects the hypothesis that insiders achieve positive abnormal returns, with statistically insignificant results and, in some cases, negative abnormal returns. However, in the period upon which the data sample is based, the requirement for reporting of insider trades on the Oslo Stock Exchange was restricted to quarterly submission of insider activity. Thus, the study provides no evidence on short-term market reactions to insider trades on the Oslo Stock Exchange.

2.5 Insider trading and market reactions

One drawback of the earliest research on insider trading is that it mostly focuses on long-term abnormal returns and whether insiders are able to predict future security prices and thereby outperform the market. Although it gives a good indication on the information content of the trades, it does not contribute towards explaining immediate market reactions. This can, foremost, be explained by historic regulations regarding reporting of insider trades allowing for longer delays in reporting. In the studies mentioned above, the lag from a trade is executed until it is reported is generally large and the market reactions from the trade is thereby difficult to isolate.

More recent studies that examine the short-term price implications of insider trading include Fidrmuc et al. (2006), who investigated the UK stock market. For insider purchases, the CAAR for their sample was 1.65 per cent, whilst sales show a coefficient of negative 0.49 per cent. Lakonishok and Lee (2001) also examined short-term price reactions to legal insider trades, but for the US Stock Exchange. However, they only found marginal short-term abnormal returns of 0.59 per cent, but highlight that the lag from slow reporting likely has implications. Aktas et al. (2008) also examined the US stock market and conclude that financial markets have a weak but significant response to insider purchases with a 0.52 per cent CAAR for insider purchases, whilst insider sales gave an unexpected positive sign. Furthermore, Aussenegg and Ranzi (2008) conducted a multi-country study on the short-term price impact of insider trading in continental Europe. This study also finds that there are both significant negative returns following insider sales and positive returns following insider purchases. Mutual for these studies is that the magnitude of abnormal returns from insider purchases tend to be much larger than for insider sales, with absolute CAARs for purchase transactions being at least twice as large. Furthermore, both Fidrmuc et al. (2006) and Lakonishok and Lee (2001) provide evidence that abnormal returns tend to be greater for larger transactions.

Overall, previous literature is somewhat ambiguous as to whether insiders are able to predict future share prices and achieve abnormal returns. However, a majority conclude that insiders obtain abnormal returns on their trades compared to the market, indicating that the trades contain information that is not yet reflected in the market. In an efficient market, this should yield market reactions. Studies investigating short-term price reactions present ambiguous results on the implications of insiders sales. However, they all find significant positive abnormal returns to insider purchases, although of different magnitude. Furthermore, although there is evidence that Oslo Stock Exchange insiders fail to obtain long-term abnormal returns, short-term market reactions from insider trades on the Oslo Stock Exchange are yet to be investigated.

2.6 Insider trading and volume

In comparison with previous literature examining properties of returns to measure abnormal performance, there is significantly less research investigating the distribution of trading volume. Trading volume also plays a crucial part in financial markets and contributes towards uncovering investors' response to information. Furthermore, abnormal volume can capture deviations in market reactions for different investors that are eased out in daily returns. Chae (2005) investigated abnormal trading volume post both scheduled and unscheduled information-generating events, including earning announcements, target and merger announcements and Moody's ratings. He found an increase from daily trading volume ranging from 5.40 to 98.63 per cent on the announcement date.

Further, some researchers have investigated abnormal trading volume in presence of asymmetric information. Chae (2005) also discusses this by looking at abnormal volume prior to information-generating events to explain how investors respond to asymmetric information. He found that before scheduled announcements, trading volume decreased by approximately 15 per cent whilst trading volume increased prior to unscheduled announcements. This suggests that trading volume increase in information asymmetry. Kyle (1985) investigates the liquidity characteristics during insider trading by using a dynamic model with sequential auctions. He finds that abnormal trading volume is higher prior to information-generating events with a higher degree of information asymmetry. In contrast, Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) study interday variation in volume and find that trading volume can actually decrease in the presence of information asymmetry.

To our knowledge, no existing literature explores the implications of insider trading on abnormal volume. However, on the back of literature examining other information generating events, it seems reasonable to assume that insider trades could lead to abnormal trading volumes following a reported insider trade. Furthermore, it is interesting to investigate whether abnormal trading volumes are higher on MERK, assuming that market participators are more information sensitive to stocks listed on this exchange. It is therefore in our interest to analyse whether we observe any abnormal trading volumes in connection with insider trades and whether they deviate across Oslo Stock Exchange marketplaces.

2.7 Insider trading and information asymmetry

In this thesis, we speculate that information asymmetry is greater on Merkur Market, which potentially can yield abnormal market reactions. Although there is no previous literature investigating deviations in market reactions across marketplaces, there is some research examining the effect of information asymmetry using different proxies. A selection of such literature will be reviewed in the following part.

It is reasonable to assume that for insiders to be able to gain from legal trades there must be a form of asymmetric information that insiders are in a position to exploit. With this in mind, increased information asymmetry should likely be correlated with higher insider gains. Overall, findings from related literature seem to support this logic. Aboody and Lev (2000) research insider gains when treating R&D activities as a source of asymmetric information. They find that abnormal returns are significantly higher for R&D-intensive companies, with a monthly mean raw return of 5.49 per cent for firms with R&D against 4.47 per cent for firms without R&D. The study also finds evidence that investors' reactions are stronger to insider trading announcements for R&D-intensive firms, which suggests that there is a higher degree of information asymmetry in these firms and that inside information is not reflected in advance of the trade.

Hong et al. (2000) hypothesise that there should be greater momentum in securities where information travels more slowly and use firm size and analyst coverage to test this. When looking at size they find that, with the exception of firms with market capitalisation below $7 million, small firms have significantly higher momentum profits with 1.43 per cent monthly raw returns for small companies, against zero for the largest firms. The findings are similar for analyst coverage, where there is evidence of more momentum in the low coverage stocks with a monthly difference of 0.42 per cent. These findings are further supported by Chari et al. (1988) and Brennan and Subrahmanyam (1995).

Considering the evidence that higher levels of information asymmetry lead to increased insider gains, it is possible that market reactions are higher on Merkur Market.

2.8 Insider trading on the Oslo Stock Exchange

In sum, corporate insiders occasionally possess information that is material to the value of the firm. Seeing that these individuals likely have a superior understanding of the underlying value of firm assets, it is natural to hypothesise that their market activities contain some information about the direction of the price of a security. As outlined in the literature review above, there is plentiful evidence indicating that insiders achieve abnormal returns from their trading activities. This suggests that the information content in reported insider trades can be material for the future price of a security, which should cause short-term market reactions according to the market efficiency theory. Evidently, there is also previous literature that finds such adjustments in the form of short-term abnormal returns post insider trades. It is reasonable to assume that also market reactions in the form of abnormal trading volumes might be observed around insider trades, although not investigated specifically. This leads us to our first hypothesis:

HYPOTHESIS I: Insider trades on the Oslo Stock Exchange cause short-term market reactions.[6]

Furthermore, previous research shows that large insider transactions lead to higher abnormal returns and that price adjustment is larger for insider purchases than for insider sales. On the back of this, it is in our interest to investigate whether this holds for the Oslo Stock Exchange through hypothesis II and III:

HYPOTHESIS II: Market reactions to insider trades on the Oslo Stock Exchange are stronger following large transactions.

HYPOTHESIS III: Absolute market reactions to insider trades on the Oslo Stock Exchange are higher for purchase transactions than for sales transactions.

The main purpose of this study is to investigate the effect of being listed on MERK on market reactions to legal insider trades. The degree of information asymmetry is proven to affect market reactions, both in the sense of insider gains and trading volume. The consensus from previous literature is that a higher degree of information asymmetry results in increased market reactions to information-generating announcements. Given that Merkur Market aims to enable small, high-growth companies, we believe that market reactions will be stronger due to the characteristics of the marketplace. Furthermore, we wish to investigate whether part of the potential stronger market reactions are actually caused by being listed on Merkur Market, seeing that regulations are more lax. With this in mind, we lastly hypothesise the following:

HYPOTHESIS IV: Market reactions to insider trades are stronger on MERK than on XOSL.

HYPOTHESIS V: Being listed on MERK leads to stronger market reactions from insider trades than being listed on XOSL.

[6] Oslo Stock Exchange here comprises the whole sample consisting of both XOSL and MERK. By market reactions we mean abnormal returns and abnormal trading volume.

3 Data

In this chapter, we present our data sources and the assumptions made in the data cleansing process, before we elaborate on the construction of our data sample. First, we give an overview of the collection of data on insider trades before the data on stock prices and other company variables are explained. We then present summary statistics of our data sample. Lastly, we present the Propensity Score Matching methodology and how we have conducted the matching applied in our cross-sectional regression analysis.

3.1 Insider trading data

The insider trades are collected from NewsWeb raw data provided by the Oslo Stock Exchange. The raw data consists of string text from which all variables have been extracted manually. The original dataset consists of 4,396 "mandatory notifications of trade primary insiders" from the period 01.01.2017 to 28.02.2020. There are two main arguments for choosing this time interval. Firstly, we have excluded 2016, as the first year of trading on Merkur Market is characterised by a low number of insider trades and small transaction volumes. Secondly, we have not included any insider trades occurring after February 2020, due to the COVID-19 pandemic.[7]

The notifications contain date and time of announcement and transaction, the exchange where each company is listed at the time of transaction, issuer sign (Oslo Stock Exchange ticker), transaction price, transaction volume, whether the transaction was a sale or purchase, currency, insider name and position and insider holding post transaction. Furthermore, ISIN codes are added for matching purposes. The dataset contains insider trades executed in securities listed on XOSL, XOAS (Oslo Axess) and MERK. The number of companies represented in the raw data amounts to 258. We exclude all insider trades from companies listed on XOAS, as the focus of the thesis is XOSL and MERK. Companies delisted after or during the period analysed are included in the dataset. All insider trades with a transaction value below NOK 125,000 (Norwegian Krone) are excluded, as transactions of low value give a weaker insider trading signal according to Lakonishok and Lee (2001). We deem this amount to be adequately large to avoid

[7] The Oslo Stock Exchange Benchmark Index (OSEBX) experienced an overall decrease of 14.8 per cent through March 2020 despite a 16.8 per cent recovery the last two weeks of the month (Aase, 2020).

transactions without information content, while still allowing for a sufficient number of Merkur Market transactions. Furthermore, from manual inspection of the trades, we discovered that the aforementioned requirement from the Norwegian Financial Supervisory Authority of reporting insider trades no later than before market opening the next trading day is violated in several instances in our dataset. Events reported as late as 120 days after the trade occur in our raw data. As the main event window applied in our analysis starts two days prior to an event[8], we remove all events notified more than two days after their transaction date. Furthermore, extreme outliers in terms of transaction values have been removed.

All insider trades in shares or options from employee share purchasing programmes, executive remuneration, private placements, seasoned offerings, gifts, or company internal transactions have been excluded from our dataset, as we are interested in analysing the effect of non-anticipated and information-generating insider trades. Lastly, all duplicate notifications and trades conducted on exchanges apart from the Oslo Stock Exchange in currencies other than NOK have been removed.

3.2 Stock price data

Company data has been collected from Refinitiv Eikon. The dataset consists of daily observations of the closing price adjusted for dividends and stock splits, market value (mCap), volume traded, outstanding shares (free float) and Book-to-Market ratio in the period 30.06.2016 to 01.04.2020. All companies listed on XOSL and MERK in the period are included in the dataset. The applied time frame allows us to calculate normal returns for insider trades occurring early in 2017 and late February 2020. According to MacKinlay (1997), the use of daily observations is preferred when there is no uncertainty regarding the event date. The process of cleaning and structuring the data uncovered a few occurrences of the closing price data not being adjusted for stock splits for very short intervals. Closing price in these incidents has been interpolated using closing price prior to the split. Lastly, our company data does not include days where OSE is closed for trading. Consequently, we have adjusted the notification delay data for this, preventing these days to drive up the mean of this variable.

[8]Further explained in Section 4.

According to MacKinlay (1997), calculation of normal returns in an event study should be conducted using a broad-based stock index. Consequently, we have chosen to utilise the Oslo Stock Exchange All-share Index (OSEAX) for this purpose. This index consists of all shares listed on XOSL, and the daily number of outstanding shares of its constituents is applied in this value-weighted index. The index is further adjusted for dividend payments and other corporate actions (Oslo Stock Exchange, 2020c).

In order to categorise the companies by sector, we have used the Oslo Stock Exchange sector classification as a basis and made some generalising adjustments. Due to the limited size of our event dataset, we found it necessary to merge some sectors into more general categories, allowing a greater number of observations per sector. The 12 sector classifications provided by the Oslo Stock Exchange has been merged into six new sectors. Table 1 illustrates the new sector classifications.

Table 1: Merged industries

The table illustrates the merged industries based on the Oslo Stock Exchange sector classifications. The 12 sector classifications provided by Oslo Stock Exchange has been merged into 6 new industries.

Finance	Energy	Industrials	Consumer Goods	Healthcare	Technology
Finance	Energy	Industrials	Consumer Discretionary	Healthcare	Information Technology
Real Estate	Utilities	Materials	Consumer Staples		Communication Services
Equity Certificates					

3.3 Descriptive data

The final dataset applied in our analysis consists of 1,305 insider trades, with a total of 1,104 stock purchase transactions and 201 sales. Table 2 gives an overview of the relationship between transactions on XOSL and MERK. Descriptive statistics for the full dataset across sell/purchase activity, sell/purchase aggregated for XOSL and MERK and correlation matrices can be found in Tables 12, 13, 14 and 15 in the Appendix. From Table 2, we can clearly see that the mean and median transaction values are both higher for sales transactions on XOSL, compared to purchases on the same exchange. When collecting our data, we observed a substantial amount of sales transactions being triggered by an insider leaving the company, thereby selling a large fraction, if not all, of their equity in the firm. Hence, this relationship is economically intuitive. For MERK, the sales transactions do show a higher median value compared to to insider purchases, but this relationship turns when examining the mean transaction values. The high mean transaction value on Merkur Market purchases could be explained by that even though we have removed transactions with extreme monetary value, there remains some large transactions in the dataset, driving the mean upward to some extent.

Table 2: Descriptive statistics by exchange and transaction type

The table illustrates the mean, median, standard deviation, min and max values of variables market capitalisation (in mNOK), daily traded volume (in thousands), daily turnover, book-market-ratio, transaction value (in tNOK) and notification delay (amount of days from transaction to notification on NewsWeb), respectively, for purchase and sales transactions on MERK and XOSL.

	Mean	Median	SD	Min	Max
MERK Purchase ($N = 40$)					
mCap	1,648	385	2734	44	9,979
VOL	157.82	23.50	272.68	0.00	1009.30
Turnover	0.00284	0.00061	0.00445	0.00000	0.01798
Book-Market	0.527	0.322	0.533	0.028	2.564
Transaction value	5,972	567	12,327	137	51,000
Delay	0.57	0.00	0.78	0.00	2.00
XOSL Purchase ($N = 1064$)					
mCap	12,157	2,773	47,824	44	534,686
VOL	958.97	155.00	2,464.52	0.00	22,382.40
Turnover	0.00454	0.00172	0.01124	0.00000	0.17126
Book-Market	0.809	0.619	0.580	-0.455	4.000
Transaction value	4,379	510	25,511	125	675,000
Delay	0.22	0.00	0.43	0.00	2.00
MERK Sale ($N = 6$)					
mCap	728	451	897	85	2499
VOL	114.52	56.20	188.08	0.00	492.40
Turnover	0.00290	0.00310	0.00283	0.00000	0.00608
Book-Market	0.357	0.280	0.240	0.061	0.758
Transaction value	2,091	2,063	1,001	929	3,675
Delay	0.67	1.00	0.52	0.00	1.00
XOSL Sale ($N = 195$)					
mCap	31,727	2,945	119,475	65	711,802
VOL	983.64	233.70	2,346.08	0.00	22,382.40
Turnover	0.00613	0.00225	0.01348	0.00000	0.10096
Book-Market	0.502	0.377	0.525	-0.490	2.222
Transaction value	15,570	1,073	85,109	126	1,066,646
Delay	0.32	0.00	0.50	0.00	2.00

Figure 1: Distribution of insider purchases

The figure illustrates all insider purchases registered in our dataset on XOSL and MERK through the period 01.01.2017 – 28.02.2020 by month, size, industry and company position. Bars marked "M" illustrate MERK-data, while bars marked "O" illustrate XOSL-data. Size is defined as follows: low is transaction volume in the interval NOK 125,000 - NOK 500,000. Medium transaction interval is NOK 500,000 - NOK 2,000,000 and large transactions are transactions above NOK 2,000,000. The sector classifications originates from Table 1.

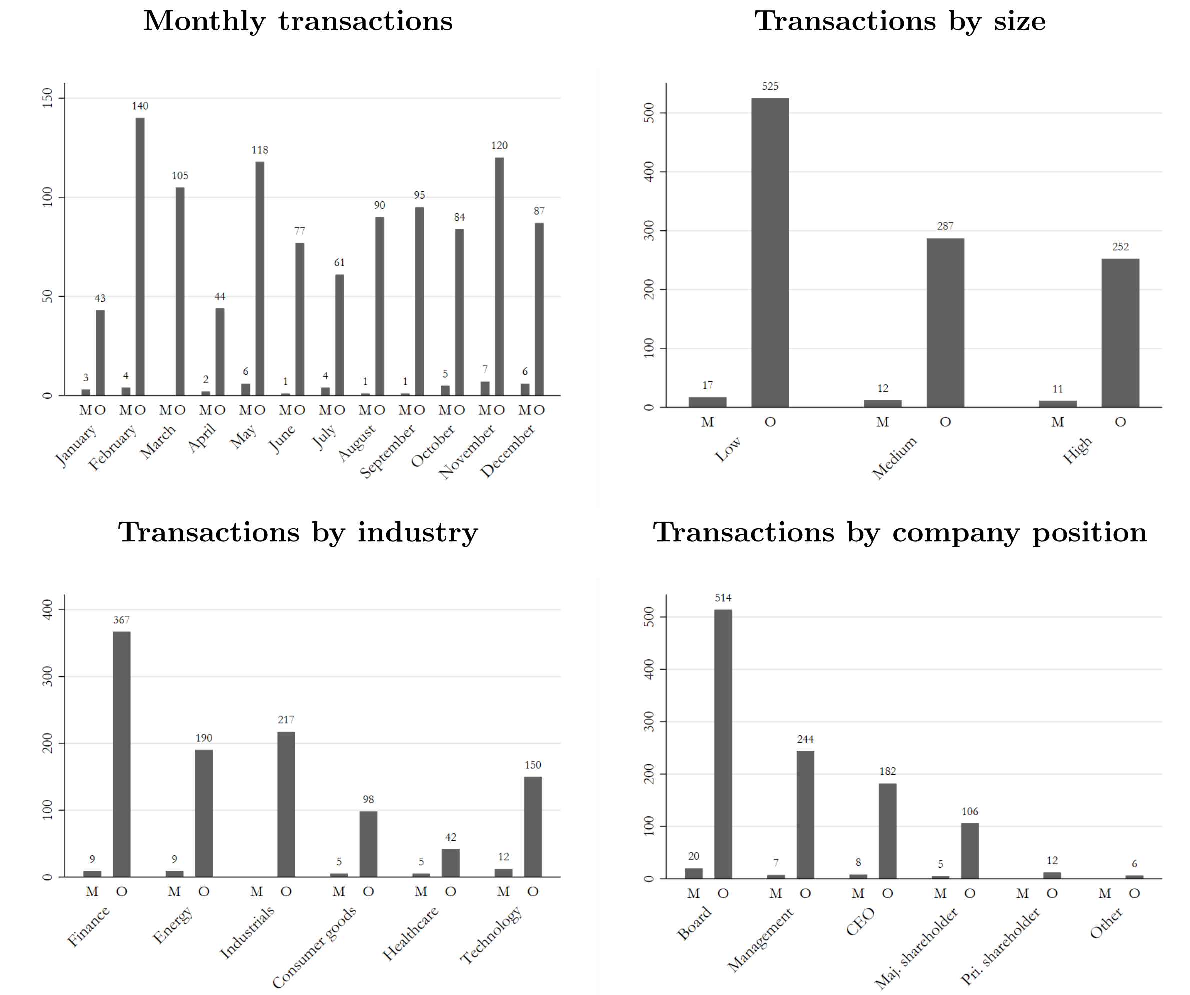


Figure 1 presents descriptive data of purchase transactions by month, monetary size, industry of the stocks traded and company position of the inside trader. The chart of monthly transactions includes data from 2017, 2018, 2019 and the first two months of 2020. Despite low amount of insider purchases in January, the effect of including the 2020 data is illustrated by the substantial amount of insider trades in February compared to the remaining months. The figure showing transactions by size illustrate the distribution of the transaction size in the sample. Low transaction volumes are defined as transactions in the interval NOK 125,000 - NOK 500,000. The medium transaction interval is NOK 500,000 - NOK 2,000,000 and large transactions are transactions above NOK 2,000,000. From Figure 1, the transactions are relatively evenly distributed across the transaction size categories. For industries, there seems to be a majority of transactions within Finance, where we experienced a large presence of mid-sized transactions in equity certificates[9] when registering the insider trades. Furthermore, the graph chart illustrates the absence of transactions within the Industrials classification for MERK-listed companies. The insider trades are mainly driven by transactions by the Board of Directors. The numbers of transactions from primary shareholders and employees outside management (Other) are marginal. Many of the registered trades from employees outside management disappeared when setting the cap on transaction size, as many of these were smaller trades. For primary shareholders, many hold majority positions in the companies and are therefore categorised as majority shareholders.

3.4 Propensity score matching

In order to perform a more precise estimation of the effect announced insider trades has on companies listed on MERK versus XOSL, we will match companies on MERK with similar companies on XOSL using propensity score matching. The method was first introduced by Rosenbaum and Rubin (1983), and is a widely used approach to estimate the causal effect of a treatment in observational studies (Abadie & Imbens, 2016). In the following part, we only include insider purchases due to the low amount of insider sales transactions on MERK.

According to Caliendo and Kopeinig (2008), a major concern in our empirical study, caused by its design, is the inability to observe how the returns of companies listed on MERK would react to mandatory notifications of insider trades, had the stocks been listed on XOSL. As the treatment in our study is defined as being listed on MERK, and the control group being XOSL-listed companies, we are unable to observe the counterfactual outcome of the treated firms. The returns of the stocks in our study are likely to be correlated with what marketplace each company is listed on, entailing a possible problem of endogeneity caused by a selection bias of the treated and the control group. As we want

[9]Equity certificates are shares issued by savings banks listed on XOSL and MERK.

to interpret our results causally, the firms need to be matched on a set of characteristics in order to create a sample of similar treated and untreated stocks, according to Angrist and Pischke (2009).

3.4.1 The PSM model

The propensity score is the conditional probability of assignment to a particular treatment given a vector of observed covariates (Rosenbaum & Rubin, 1983). To estimate the propensity score of each event, we apply a probit model, as Caliendo and Kopeinig (2008) argue that probit and logit models yield similar results in cases with binary treatment. In the PSM model, the dependent variable is the binary variable for treatment (D), and the firm characteristics we wish to match on between the two groups act as the independent variables used in the model. The model applied is derived from Caliendo and Kopeinig (2008). The expression for the propensity score is expressed as follows:

$$p(x) = prob(D = 1|x) = E(D|x) \quad (1)$$

We use the binary variable MERK as the treatment variable D. This variable equals one if a company is listed on Merkur Marked and, thus, is "treated", and zero if listed on XOSL. The independent variables applied in the PSM are chosen by their ability to identify stocks listed on XOSL with similar characteristics as stocks listed on MERK. The intention is to create pairs that would have had similar market reactions in the applied event window if they were both listed on XOSL. The applied independent variables are explained below:

Turnover, calculated as shares traded over number of outstanding shares, is included as higher trading volume can be an indicator of higher liquidity, which in turn could reduce movement in share price due to high volume transactions.

Market Capitalisation could be linked to stock liquidity and price movement. As illustrated in Table 2, there are great differences in mean and median market capitalisation between MERK and XOSL. Thus, creating a matched sample with companies of more similar market value will be necessary to compare the returns from events on the two exchanges.

Book-to-Market (BM) ratio is included in the matching as it can be used as an indicator of whether a company is a growth stock (low BM) or a value stock (high BM). Rozeff and Zaman (1998) found an overreaction in returns post announced insider trades in US growth stocks compared to value stocks.

Industry classification is included in the matching as we expect companies within the same sector to react similarly to announced insider trades. Furthermore, companies of the same classification are affected by the same trends within their sector. MERK-listed companies are matched only with XOSL-listed companies within the exact same sector in order to remove the possibility of cross-industry matching. Lastly, Table 17 in the Appendix advocate for exact matching, as we see a significant differences in mean CAR and CAV for each industry.

In order to match the pairs of companies after the propensity score is calculated for each individual event, we employ the Nearest Neighbour (NN) matching algorithm. This algorithm pairs the firms which are closest to one another based on their estimated propensity scores (Caliendo & Kopeinig, 2008). Furthermore, there are two options when matching with this model: whether or not to perform matching with or without replacement. If we allow MERK events to be matched against multiple XOSL events, we allow for replacement. With great difference in propensity scores between the two populations, not allowing for replacement could increase bias, as it might become difficult to find a proper match, according to Caliendo and Kopeinig (2008). This is an especially relevant challenge when there are few non-treated observations compared to treated. As illustrated in Table 2, the sample of XOSL-events constitutes the majority of all notifications of insider purchase transactions in our dataset. Thus, we choose to use NN without replacement, as we believe the bias mentioned above is limited in our case.

3.4.2 Matching quality and model assumptions

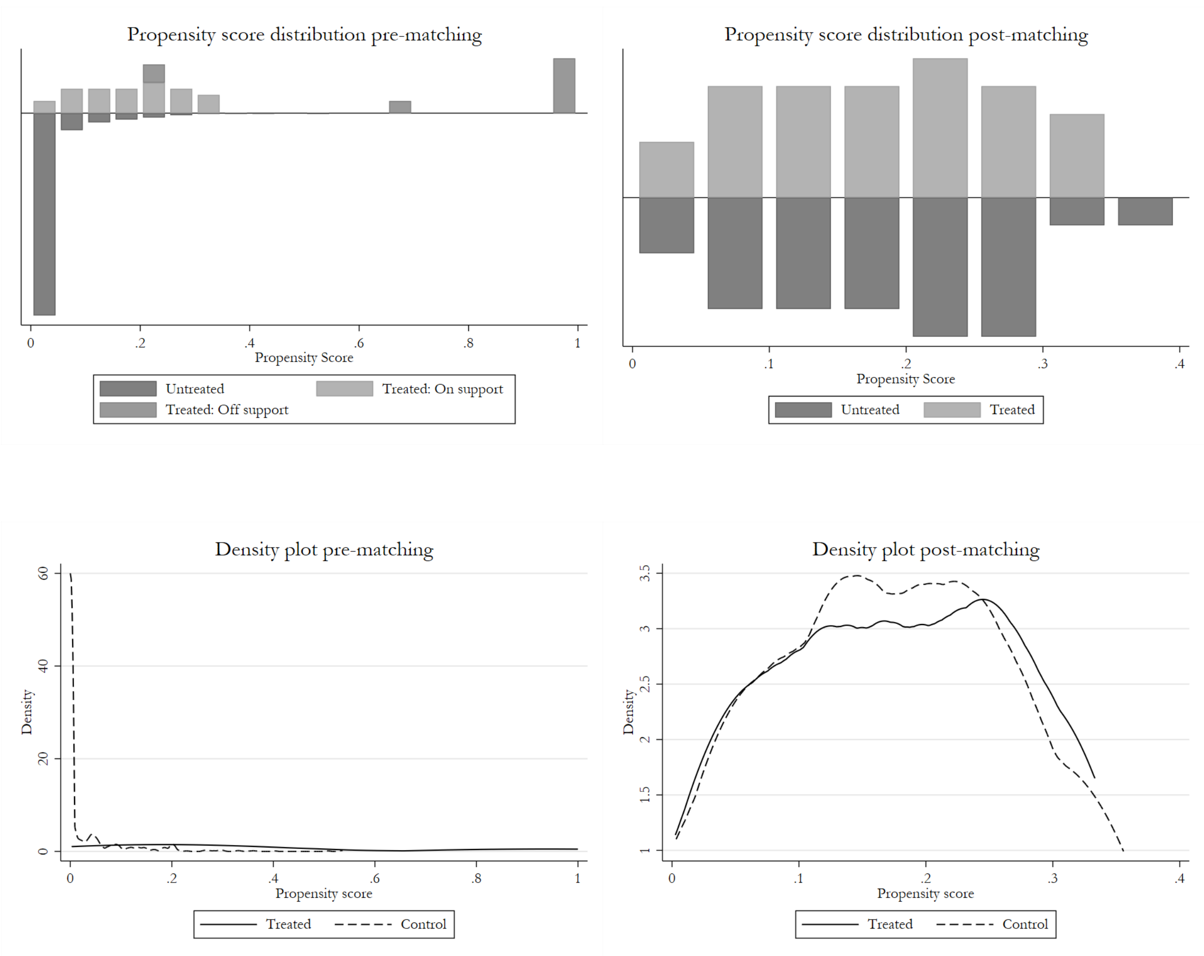
There are three main underlying assumptions in the PSM model. The first is the conditional independence assumption. This assumption implies that systematic differences in outcomes between treated and control group individuals with the same values in covariates are attributable to treatment (Caliendo & Kopeinig, 2008). As the design of our model does not allow us to observe any pre-treatment characteristics of the companies listed on Merkur Market, we are unable to observe the effect of treatment compared to pre-treatment data.

Thus, it is challenging to argue that this clearly strong assumption of random treatment assignment is met. Still, for the rest of our analysis, we assume the condition to be valid.

A second assumption is the common support assumption, which states that there are both untreated and treated observations for every value of x. In order to test this assumption, we need to evaluate whether the ranges of propensity scores for the two populations overlap. This can be done through a visual inspection of the density distribution of propensity scores for the matched/unmatched control group and the treated group, according to Lechner (2001). Figure 2 illustrates the distribution of propensity scores pre and post-matching, with histograms on the first row and density plots on the second. As illustrated in the figure, the pre-matching distributions (left-side charts) are differing to a great extent. The majority of propensity scores in the untreated group (XOSL-listed firms) are very low. Furthermore, the treated scores pre-matching are more evenly distributed, with some observations of very high propensity score. In order to meet the common support assumption, we follow Smith and Todd (2005) and trim the propensity score densities, requiring that the densities exceed zero by a threshold amount of 2 per cent. The trimming removes the observations marked "Treated: Off support" in the upper left chart in Figure 2, in line with Bryson et al. (2002) stating that individuals that fall outside the region of common support have to be disregarded from the analysis. Thus, after matching, as illustrated in the two right charts of Figure 2, we see that the propensity score distribution and density plot between the treated and control group exhibit a relatively satisfactory overlap. On the back of this, we conclude our visual inspection by stating that the common support assumption is satisfied in our matched dataset.

Figure 2: Distribution of propensity scores pre- and post-match

The figure illustrates the distribution of propensity scores pre (left) and post (right) propensity score matching. Propensity score densities are trimmed at a minimum 2 per cent threshold, removing all observations off common support. This is illustrated in the upper left figure. The upper row presents histograms, while the lower includes charts of density plots.



A third and final important assumption, named the "balancing condition", states that one should observe the same x-characteristics, given the same propensity score (Caliendo & Kopeinig, 2008). This condition is evaluated by comparing the similarity of treated and non-treated observations after matching, based on the pre-treatment characteristics. Again, missing pre-treatment characteristics for the treated group, this assumption is hard to test. Nevertheless, Table 3 provides a clear overview of the difference between the matching variables before and after matching. The table illustrates large deviations in market capitalisation, Book-to-Market ratios and turnover pre-matching. Furthermore, the t-test comparing the mean value of the treated and control, unmatched and matched, illustrates that the mean value of the Book-Market variable pre-matching is statistically different between the two groups.

When we evaluate the post-matching data in Table 3, we see that the matching algorithm has, to some extent, been able to balance the independent variables of the MERK-listed and XOSL-listed companies. The observed characteristics are more similar post-matching; none of the mean values for the two groups are statistically different. According to Caliendo and Kopeinig (2008), the bias between the treated and control groups post-matching should not exceed 5 per cent in order to be seen as sufficient. Thus, the bias in the matched sample variables are not sufficient, except for market capitalisation.

As MERK-listed companies are matched only with XOSL-listed companies within the exact same sector in order to remove the possibility of cross-industry matching, the industry classification matching is not illustrated in Table 3 as the mean values of this dummy-matching is irrelevant, and the bias for all five matched sectors equals zero post-matching.

If we do not accentuate the poor bias percentages for the matching variables, we find the propensity score model applied and the Nearest Neighbour algorithm without replacement to be sufficient in terms of defining a control group of events from the XOSL with approximately similar characteristics as the treated MERK-group.

Table 3: Descriptive statistics PSM

The table presents descriptive data on firm characteristics from MERK, XOSL and a matched sample selection from XOSL. mCap is market capitalisation in mNOK, Book-Market is the Book-to-Market ratio and turnover is (Daily Volume/mCap). There are no MERK-companies within the Industrials-sector. Thus, events within this sector are not included in the post-matching sample.

	Unmatched/	Mean		%	% red.	t-test		V(T)/
	Matched	Treated	Control	Bias	Bias	t	p>|t|	V(C)
mCap	U	1647.9	12777	-29.8		-1.33	0.183	0.00*
	M	1074.8	1487.7	-1.1	96.3	-0.69	0.495	0.47
Book-Market	U	.52732	.78877	-48.0		-2.92	0.004	0.92
	M	.49164	.55731	-12.1	74.9	-0.36	0.719	0.88
Turnover	U	.00284	.00462	-22.1		-1.07	0.284	0.18*
	M	.00425	.00324	12.6	42.9	0.60	0.548	0.52

* if variance ratio outside [0.53; 1.89] for U and [0.45; 2.23] for M.

4 Methodology

In this section, we describe the methodologies applied to examine abnormal returns and trading volume related to legal insider trades on the Oslo Stock Exchange, and whether being listed on Merkur Market affects abnormal returns and turnover. We will begin this section by elaborating on the event study methodology used to measure abnormal market reactions around announcements of insider transactions. First, we define our event, estimation window and event windows, before we explain the calculation of abnormal returns and abnormal volume.

Furthermore, the section presents the methodology behind the cross-sectional multiple regression that is used to analyse the effect of being listed on MERK on market reactions from insider trades, first on the full sample and further on the matched XOSL sample to allow for causal interpretation.

4.1 The event study methodology

The event study methodology has been applied to investigate hypothesis I-III of the thesis and further to obtain the dependent variables for the regression analysis. This finance methodology is widely used to examine short-term market behaviour around events such as regulatory changes, earning announcements or other exogenous events. In general, the methodology is used to test how the market incorporates information and to measure the impact an event has on shareholder wealth. For the intent of this thesis, the methodology is applied to investigate security price and volume behaviour around announcements of insider trades on the Oslo Stock Exchange. The approach described in the following is derived mainly from that described by MacKinlay (1997). For measuring abnormal volume, we use a methodology derived from Chae (2005) and Campbell and Wasley (1996).

Underlying the event study methodology there are three important assumptions. First, the market where the events take place is semi-efficient, implying that new information is reflected instantly in the stock price. Second, the events analysed are exogenous. Third, the market price on the event date is only affected by the event analysed.

4.1.1 Defining events

The first step in conducting an event study is to define the events to be analysed (MacKinlay, 1997). As presented in Section 3, the events assessed in this thesis are trades conducted by primary insiders on XOSL and MERK. As these trades are unscheduled events, the exogeneity assumption seems to hold.

4.1.2 Event window

The event window is defined as the time interval in which the market effect of the event is studied. According to MacKinlay (1997), it is beneficial to include more days than the event date itself when constructing the event window. The reasoning behind this is the possibility of information leakage before the event in question and lagged market reactions. With regard to insider trades, the greater issue is the possibility of lagged reporting. As discussed in Section 2, insiders are obliged to report their trades before the opening of the stock exchange the following trading day. However, there are instances where insider trades are published on NewsWeb with a greater lag. To deal with this issue, we include the two days before the announcement in the event window and have removed all trades where the lag from the trade is made until the announcement exceeds two days. Including two days in advance of the insider trades allows for the analysis to capture the full reaction from the events, should the market react before the announcement. Furthermore, the assumption of market efficiency advocates for an expansion of the event window beyond the event date being unnecessary. However, as daily expected returns are close to zero, according to Fama (1998), a short window including some days after the event is advantageous in case of small lags in market reactions.

The approach applied in this thesis is to explore several smaller event windows ranging from two days before (-2) to three days after (+3) the event date.

4.1.3 Estimation window

According to MacKinlay (1997), the window used to estimate normal returns must not overlap the event window. Observed returns from the event window could have an impact on the normal return, biasing the analysis. Consequently, according to Binder (1998), a buffer of at least one day should exist between the estimation and event window.

The estimation window should further include a certain number of observations in order to reduce the variance of calculated cumulative abnormal returns, according to MacKinlay (1997). However, he argues, too wide an estimation window increases the probability of including similar events within the same period of time. We use a 90-day estimation window ending 20 days before the event date. This estimation window is slightly shorter than that recommended by MacKinlay (1997) due to the regularity of insider trades, especially on XOSL. Thus, we require observable share prices for all days of the estimation window.

4.1.4 Measuring abnormal returns

4.1.4.1 Calculating returns

The returns used in the event study of this thesis are calculated as the percentage change in closing price from one day to the next. Following Brown and Warner (1985), we perform our analysis using arithmetic returns. The reason for using arithmetic returns over logarithmic returns in the event study is due the the aggregation of returns across securities. The calculation is illustrated in Equation (2):

$$R_{it} = \frac{P_{it} - P_{it-1}}{P_{it-1}} \tag{2}$$

R_{it} is the arithmetic return on company i on day t, P_{it} is closing price of company i on day t and P_{it-1} is closing price of company i on day $t-1$.

4.1.4.2 Modelling normal returns

An estimation of the market value of a stock in absence of the event is necessary in order to assess the effect insider trades have on the market value of the firm. According to Kothari and Warner (2008), event studies are, to a great extent, immune to misspecifications in estimating expected return. Consequently, they argue, that abnormal announcement returns cannot be attributed to the problem of model misspecification. The one-factor market model, according to MacKinlay (1997), removes the portion of the return related to variations in the market, thereby reducing abnormal return and providing increased ability to detect event effects. Based on these arguments, we apply the market model when estimating normal returns. We regress returns for each stock of firms with insider trades on the return of the Oslo Stock Exchange All-share Index (OSEAX). For security i, the market model is specified:

$$E(R_{it}) = \alpha + \beta_i E(R_{mt}) \tag{3}$$

Where R_{mt} and R_{it} are period t market return and stock i return, respectively.

4.1.4.3 Abnormal returns and event portfolios

Abnormal returns of share i on day t has to be statistically significant to allow rejection of the null hypothesis. Abnormal returns are calculated as:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{4}$$

$AR_{i,t}$ is the difference between the actual returns in the specified event window and the expected return calculated using the market model. As we apply an event window of multiple days in our analysis, the abnormal returns must be aggregated. Cumulative Abnormal Return for company i on day t within event window $[T_3, T_4]$ is given by the equation:

$$CAR_i(T_3, T_4) = \sum_{t=T_3}^{T_4} AR_{it} \tag{5}$$

Due to the presence of overlapping event windows in insider trades on the Oslo Stock Exchange, we aggregate the abnormal returns for events with the same announcement day and create equally weighted portfolios. This approach is suggested by (MacKinlay, 1997) as a method to deal with cross-correlation of the abnormal returns.

$$CAR_p(T_3, T_4) = \frac{1}{N} \sum_{i=1}^{N} CAR_i(T_3, T_4) \tag{6}$$

Aggregating CAR for all i with the same (T_3, T_4). Further we use the CAR from the equally weighted portfolios to calculate the cumulative average abnormal returns (CAAR):

$$CAAR = \frac{1}{N} \sum_{p=1}^{N} CAR_p(T_3, T_4) \tag{7}$$

4.1.4.4 Significance testing

In order to test whether CAARs are significant, we use the test estimator explained by MacKinlay (1997), a version of the standard t-test, but make the adjustment to use the estimation window variance:

$$\theta_1 = \frac{CAAR(T_3, T_4)}{\sqrt{var(CAAR(T_1, T_2))}} \sim N(0, 1) \tag{8}$$

According to Boehmer et al. (1991), an event-induced variance affects the strength of the traditional event study methodology, causing rejection of H0 of zero abnormal returns too frequently. Thus, the cumulative average abnormal returns within event window T_3 to T_4 are divided by the standard deviation from the estimation window T_1 to T_2.

4.1.5 Measuring abnormal volume

4.1.5.1 Calculating daily volume

In line with Chae (2005), Campbell and Wasley (1996) and Cready and Ramanan (1991), we use a trading volume metric calculated as the natural logarithm of daily raw turnover. Raw turnover is defined as trading volume divided by outstanding shares and gives a relative measure of volume. To isolate the market reactions from the insider trade, we adjust volume on the day of the trade. This is done by subtracting the insider's trading volume from the trading day identified from the cleaning of the data. To avoid the natural logarithm of zero, a constant of .000255 is added to the raw adjusted turnover before log transformation. Log turnover is given as:

$$V_{it} = ln(\frac{n_{it} - n_{vit} + .000255}{S_{it}}) \tag{9}$$

where n_{it} is the number of shares traded in company i in period t and n_{vit} is volume traded by the insider. S_{it} are shares outstanding.

4.1.5.2 Modelling normal trading volume

Normal or expected trading volume can be estimated using different models. Campbell and Wasley (1996) present three different approaches: mean adjusted trading volume, an ordinary least squares (OLS) market model in trading volume, and an estimated generalised least squares model (EGLS) in trading volume. We use the mean adjusted trading volume in our analysis, following Chae (2005). Mean adjusted trading volume is specified as follows:

$$\bar{V_i} = \frac{1}{T}\sum_{t=f}^{t=l} V_{it} \tag{10}$$

where T is the number of days in the estimation window, f is the first and l is the last day of the estimation window.

4.1.5.3 Abnormal volume and event portfolios

When using the mean adjusted model for estimating normal trading volume, we calculate abnormal turnover as follows:

$$AV_{it} = V_{it} - \bar{V_i} \tag{11}$$

Furthermore, we accumulate abnormal turnover across the event windows and construct equally weighted portfolios for overlapping event dates in the same sense as for abnormal returns. Lastly, we aggregate CAV for the events and calculate the average across securities.

$$CAV_i(T_3, T_4) = \sum_{t=T_3}^{T_4} AV_{it} \tag{12}$$

$$CAV_p(T_3, T_4) = \frac{1}{N}\sum_{i=1}^{N} CAV_i(T_3, T_4) \tag{13}$$

$$CAAV = \frac{1}{N}\sum_{p=1}^{N} CAV_p(T_3, T_4) \tag{14}$$

4.1.5.4 Significance testing

The test used in our main analysis is a parametric test analysed by Ajinkya and Jain (1989), Cready and Ramanan (1991) and Campbell and Wasley (1996). Assuming all abnormal trading volume in company i at time t, are normal, independent and identically distributed random variables, the following test statistic is distributed student t under the null hypothesis (Campbell & Wasley, 1996):

$$\frac{CAAV(T_3, T_4)}{\sqrt{var(CAAV(T_3, T_4))}} \sim N(0, 1) \tag{15}$$

Following the methodology of Campbell and Wasley (1996) and Chae (2005), we apply the event window variance in our test statistic despite using estimation window variance for abnormal return.

4.2 Cross-sectional multiple regression

The results from the event studies allow for interpretation of market reactions, but does not allow for any causal interpretation. Nor can we conclude that market reactions are significantly different on MERK versus XOSL. To further examine the impact of a companies being listed on Merkur Market on market reactions from insider trades, we run multiple cross-sectional regression models on abnormal returns and turnover.

As these models use cumulative abnormal returns (CAR) and cumulative abnormal turnover (CAV), we perform the regressions with log-returns when calculating CAR, as CAR is not aggregated across securities and log-returns are advantageous for aggregation across days in the event window. This also allows for log-log interpretation of our control variables. We further apply the same CAV as in the event study, which is cumulative abnormal log turnover (see Equations (11) and (12)), although not aggregated into portfolios. Log-returns are calculated as follows:

$$R_{i,t} = ln(\frac{P_{i,t}}{P_{i,t-1}}) \tag{16}$$

where $P_{i,t}$ is closing price for share i on day t. Abnormal returns and CAR is calculated as in Equations (4) and (5), only now using log-returns and log index returns.

The models intend to test whether the potential effect of the reported insider trades on MERK and XOSL persists when controlling for other factors, and whether there is a causal effect between being listed on MERK and market reactions ex-post insider trades. The methodology used is OLS regression, and we perform several regressions using CAR and CAV in different event windows, as our dependent variable. We test four different models, two for returns and two for turnover:

Returns:

$$CAR[\tau_a, \tau_b] = \alpha + \beta_1 MERK_i + \epsilon_{it} \tag{17}$$

$$\begin{aligned} CAR[\tau_a, \tau_b] = \alpha &+ \beta_1 MERK_i + \beta_2 ln(mCap)_{it} \\ &+ \beta_3 BM_{it} + \beta_4 ln(Turnover)_{it} + \epsilon_{it} \end{aligned} \tag{18}$$

Turnover:

$$CAV[\tau_a, \tau_b] = \alpha + \beta_1 MERK_i + \epsilon_{it} \tag{19}$$

$$\begin{aligned} CAV[\tau_a, \tau_b] = \alpha &+ \beta_1 MERK_i + \beta_2 ln(mCap)_{it} \\ &+ \beta_3 BM_{it} + \beta_4 AbR[-10, -3]_{it} + \epsilon_{it} \end{aligned} \tag{20}$$

MERK is equal to one if the insider is trading in a company listed on Merkur Market, and zero for the reference group (XOSL). τ_a is the first day of the regressed event window, and τ_b is the last. $ln(mCap)$ is the log of market capitalisation, BM is the Book-Market ratio, $ln(Turnover)$ is the log of turnover and $AbR[-10, -3]$ is the difference between average absolute return and average absolute OSEAX return from $t = -10$ and $t = -3$. The last term in the regression models, ϵ_{it}, is a random error term which we assume, conditional on all model variables, to have an expected value of zero.

We control for market capitalisation as there are large differences between MERK and XOSL firm size and it is shown to effect market reactions from insider trades. According to Kim and Purnanandam (2006), larger companies are more closely followed by investors and analysts, entailing less information asymmetry and thereby weaker market reactions from information generating events. Further, Lakonishok and Lee (2001) find a relationship of higher returns post insider trade announcements in small companies, compared to firms with larger market value, and Atiase (1985) argues that the amount of private ex-ante information dissemination is a function of company size, implying that large cap companies are more efficiently priced than smaller firms.

Section 3 illustrates a great difference in Book-to-Market ratio on XOSL and MERK. Thus, Book-to-Market ratio is included as a proxy for a company being a growth-stock (low BM) or a value stock (high BM). Rozeff and Zaman (1998) found an overreaction in returns post announced insider trades in US growth stocks compared to value stocks.

Dierkens (1991) argues that higher intensity in trading is associated with a lower degree of asymmetric information. This suggests that less liquid stocks should be affected to a higher degree by new information, such as insider trade notifications. As the turnover on XOSL and MERK differs to a great extent, we control for the log of daily turnover in our cross-sectional regression of cumulative abnormal returns.

Stock price changes might induce insider trades, as insiders could use the opportunity to buy (sell) shares at a discount (premium). Thus, in the cumulative abnormal turnover model, we control for absolute return in the window [-10, -3], following Chae (2005).

In the regression models, we control for industry and time fixed effects, in order to adjust for possible bias. Furthermore, following Petersen (2009), we cluster our standard errors across two dimensions; company and week. SE's clustered by firm capture the unspecified correlation between events in the same firm across different weeks, while the SE's clustered by week capture the unspecified correlation between different firms in the same week. Moreover, the double clustering adjusts for overlap of event windows potentially biasing our standard errors.

5 Analysis

In this section we present the results from the event study and regression analysis. Firstly, we test hypotheses I, II and III by reviewing the short-term market reactions from legal insider trades. Here, we examine CAAR and CAAV for purchase and sell activity across different transaction sizes. Secondly, we investigate abnormal market reactions on XOSL and MERK and whether there are deviations between them.

The third part of this section presents our main analysis where we examine whether being listed on Merkur Market causes abnormal market reactions ex-post insider trades. We use a cross-sectional regression model with MERK-listed companies as the treated group. Due to the natural deviations in firm characteristics between the two marketplaces, a matched sample from XOSL is used in the model for causal interpretation of the results.

5.1 Market reactions from insider trading

When investigate the market reactions from insider trades, the test statistics for CAAR are based on arithmetic returns and estimation window variance, whilst we use logarithmic turnover with event window variance for CAAV, due to the methodological differences elaborated in Section 4. All CAAR and CAAV estimates are from equally weighed portfolios for trades with the same event date.

5.1.1 Abnormal returns from insider trading on the Oslo Stock Exchange

Table 4 shows abnormal returns for Oslo Stock Exchange companies for insider trades aggregated for MERK and XOSL. The table is divided into two panels which consist of market reactions from purchase versus sell activity. The panels further report abnormal returns for small, medium and large transactions in addition to abnormal returns for the full sample. Hereunder, small transactions are those below NOK 500,000, medium transactions are those between NOK 500,000 and NOK 2,000,000 whilst large transactions are those over NOK 2,000,000.

The abnormal returns from Panel A in Table 4 strongly support hypothesis I, that insider purchases lead to positive abnormal returns. This is further supported from the findings in Table 16 from Appendix, using log returns as a robustness test. Abnormal returns around purchase transactions are positive and strongly significant for all event windows across all transaction sizes with coefficients ranging from 0.87 per cent for small transactions on the announcement day to 2.43 per cent for medium transactions in event window [-2, 1]. These results are of economic value, comparing them to the average daily return for our sample of -0.01 per cent. In comparison to market reactions for the US Stock Exchange, Lakonishok and Lee (2001) and Aktas et al. (2008) found CAARs of respectively 0.59 and 0.41 per cent for the five days following an insider trade against 1.74 per cent in our sample.[10] In raising the question of why abnormal returns for Oslo Stock Exchange are almost three times as high, one explanation can be the deviations in reporting regulations. The lag of maximum two days in our sample allows for analysis of the aggregated implications of both the occurrence of the trade and the following announcement. In contrast, Lakonishok and Lee (2001) and Aktas et al. (2008) emphasise that there often is a large lag between the execution of a trade and the official report, which makes it impossible to interpret the accumulated effect of the insider trade. Information of the trade can have leaked during this lag and would not have been captured in their results. Furthermore, the comparative presented figures include insider trades of all sizes, whilst we look exclusively at trades above NOK 125,000.

Moreover, the findings of Fidrmuc et al. (2006) for the UK Stock Exchange are very much in line with our findings, with CAAR for event window [0, 1] of 1.16 per cent against 1.65 per cent for our sample. These findings further support the argument of the deviations in returns from the US Stock Exchange being caused by differences in reporting regulations, as their sample withholds lags of maximum five days and an average lag of zero. Furthermore, Fidrmuc et al. (2006) also investigates the implications of CAAR across different transaction sizes. Here, the CAAR for UK securities is almost twice as high as our Oslo Stock Exchange sample with 3.12 against 1.69 per cent. However, the results are not comparable as they use a relative measure when categorising transaction size whilst our categories are separated on absolute values.

One surprising finding from Panel A of Table 4 is that medium transactions yield higher

[10] All comparisons in the analysis uses CAARs from the equivalent event window from our study, to the window used by the author referred to. Here, we assume that all trades are executed on Day -2

or equal abnormal returns in comparison to large transactions for all event windows. This contradicts hypothesis II, that market reactions increase in accordance with the size of the transaction. One explanation for this can however again be the absolute size categories. It may for example be the case that medium transactions are more often performed by insiders in smaller companies, which are proven to generate higher abnormal returns (Hong et al., 2000).

The coefficients from Panel B in Table 4 involving sales transactions are both less significant and of lower economic impact, despite a much higher average transaction value with NOK 15m against NOK 4m. Firstly, some of the coefficients withholds an unexpected positive sign, which is especially apparent for insider sales in the small transaction size category. However, for medium and large sales transactions, all significant abnormal returns have a negative coefficient ranging from -0.92 to -1.78 per cent. The results indicate that large and medium insider sales are information-revealing events, but the ambiguous results for the full sample contradicts hypothesis I that insider sales yield market reactions. Moreover, Table 16 from Appendix show stronger evidence of negative abnormal returns from insider sales with a statistically significant coefficient of -0.56 per cent for event window [-2, 2] when using log returns. In addition, Panel C in Table 6 seems to report some evidence of information content in sales transactions on XOSL, where CAAR for event window [-2, 2] is negative 0.47 per cent and statistically significant.

Further, from Table 4 seems to provide evidence for hypothesis III, entailing that absolute market reactions are higher for purchase transactions than sales transactions. For the main event window [-2, 2], the absolute CAAR is more than five times higher for purchases than sales, with the sales coefficient also being economically insignificant. This is in line with the finding that have been highlighted by Lakonishok and Lee (2001), who find that US purchase transactions on average have absolute abnormal returns four times larger than their findings for insider sales and by Fidrmuc et al. (2006), who find that price reactions to purchase transactions in the UK sample are almost three times as large as for sales. One explanation for this may be that markets interpret the insider sales as withholding less information content. It may be that insider sales are interpreted as liquidation needs or risk-adjusting behaviour more than information revealing events. Furthermore, there are fewer observations for insider sales which may have implications.

In sum, we find that there are positive abnormal returns around insider purchases. The magnitude of the returns is larger than for comparable studies of the US stock market, which we expect may be due to speedier reporting and differences in regulations for the transactions in the sample. The findings for insider sales are more ambiguous, but our results indicate that absolute returns are larger for purchase transactions than sell transactions.

Table 4: Price reactions to insider trades according to transaction size categories

The table reports CAARs for insider purchase and sale transactions across transaction size categories around the event date. The sample includes all reported insider trades from 01.01.2017 to 28.02.2020 above NOK 125,000, including both MERK and XOSL. The main event window is [-2, 2] as some insider trades are reported with a two-day lag. Other event windows are included for robustness. CAARs are measured in arithmetic returns, where the market model has been utilised to calculate β with estimation window [-110, -20]. Insider trades that have the same event time have been aggregated into equally weighted portfolios to reduce covariance. Panel A reports insider purchases whilst panel B reports insider sales. The panels show CAARs for the full sample, small transactions, medium transactions and large transactions. Small transactions are trades below NOK 500,000. Medium transactions are trades between NOK 500,000 and NOK 2,000,000. Large transactions are trades over NOK 2,000,000.

	CAAR							
	[0, 0]	[0, 1]	[-1, 1]	[-1, 2]	[-1, 3]	[-2, 0]	[-2, 1]	[-2, 2]
Panel A: Purchases								
All	1.18%***	1.65%***	1.67%***	1.83%***	2.00%***	1.10%***	1.58%***	1.74%***
N=554	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Small	0.87%***	1.26%***	1.05%***	1.53%***	1.84%***	0.72%***	1.11%***	1.59%***
N=212	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Medium	1.63%***	2.12%***	2.41%***	2.02%***	2.20%***	1.95%***	2.43%***	2.03%***
N=167	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Large	1.13%***	1.69%***	1.70%***	2.02%***	2.00%***	0.76%***	1.32%***	1.64%***
N=175	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Panel B: Sales								
All	0.09%	0.42%*	-0.52%**	-0.51%**	-0.25%	-0.67%**	-0.34%	-0.33%
N=171	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Small	0.54%	1.53%***	1.13%***	1.01%***	0.71%**	0.20%	1.19%***	1.07%***
N=47	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Medium	-0.08%	0.05%	-0.94%*	-0.60%	-0.24%	-1.78%***	-1.65%***	-1.30%**
N=56	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Large	-0.09%	-0.05%	-1.32%***	-1.50%***	-0.92%**	-0.35%	-0.32%	-0.49%
N=68	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)

Standard errors in parentheses

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

5.1.2 Abnormal turnover from insider trading on the Oslo Stock Exchange

Table 5 reports abnormal trading volumes across transaction type and size for the full sample. The market reactions have been divided into the same size categories as in subsection 5.1.1, labeled Small, Medium and Large.

Panel A and B show that there are positive abnormal turnover in reaction to all reported insider trades. The positive turnover is both economically and statistically significant, where cumulative turnover increases by 6.29 per cent for insider purchases and 5.13 per cent for insider sales from estimated daily trading volume for event window [-2, 2]. There are no previous studies examining abnormal turnover ex-post insider trades. However, comparison can be made to Chae (2005) and his study on abnormal volumes in relation to unscheduled acquisition, target and Moody's ratings announcements. Chae (2005) finds that on the announcement day, turnover increases by 33.02 per cent for acquisitions, 98.63 per cent for target and 5.40 for Moody's ratings. In comparison, the increase in turnover on the event day in our sample is 2.20 per cent for insider purchases and 1.96 per cent for insider sales. Despite the magnitude of increased turnover found in Chae's study being much larger, this is expected due to the difference in information content of the investigated events. Chae (2005) examine the impact of major corporate events which reveal material information that have a substantial impact on price, while insider trades only provide an indication of the direction of the stock price. On the back of this, the abnormal turnovers from Table 5 are quite substantial given the information content.

Furthermore, Table 5 also supports hypothesis III that market reactions are stronger for purchase transactions than sales transactions, seeing that abnormal volumes are higher for purchases than sales for all event windows, with the exception of event windows [-2, 0] and [-2, 2] for large transactions.

Table 5: Turnover reactions to insider trades according to transaction size categories

The table reports CAAVs for insider purchase and sale transactions across transaction size categories around the event date. The sample includes all reported insider trades from 01.01.2017 to 28.02.2020 above NOK 125,000, including both MERK and XOSL. The main event window is [-2, 2] as some insider trades in the sample are reported with a two-day lag. Other event windows are included for robustness. CAAV is measured using log abnormal turnover, where estimated normal turnover is calculated using the mean adjusted model with estimation window [-40, -11]. The coefficients from the table give the abnormal turnover in reference to the mean. Insider trades that have the same event time have been aggregated into equally weighted portfolios to reduce covariance. Panel A reports insider purchases whilst panel B reports insider sales. The panels show CAAVs for the full sample, small transactions, medium transactions and large transactions. Small transactions are trades below NOK 500,000. Medium transactions are trades between NOK 500,000 and NOK 2,000,000. Large transactions are trades over NOK 2,000,000.

	CAAV							
	[0, 0]	[0, 1]	[-1, 1]	[-1, 2]	[-1, 3]	[-2, 0]	[-2, 1]	[-2, 2]
Panel A: Purchases								
Total	2.202***	3.421***	4.569***	5.449***	5.926***	4.191***	5.411***	6.291***
N=565	(0.10)	(0.20)	(0.27)	(0.37)	(0.46)	(0.29)	(0.35)	(0.44)
Small	2.481***	3.749***	4.991***	6.059***	6.669***	4.618***	5.886***	6.953***
N=220	(0.19)	(0.37)	(0.50)	(0.67)	(0.81)	(0.48)	(0.61)	(0.76)
Medium	1.970***	3.083***	4.285***	5.276***	5.865***	4.461***	5.574***	6.566***
N=168	(0.17)	(0.32)	(0.46)	(0.61)	(0.72)	(0.48)	(0.58)	(0.73)
Large	2.075***	3.335***	4.312***	4.855***	5.062***	3.405***	4.665***	5.208***
N=177	(0.15)	(0.33)	(0.45)	(0.61)	(0.81)	(0.54)	(0.63)	(0.78)
Panel B: Sales								
Total	1.964***	2.903***	3.650***	4.484***	4.933***	3.353***	4.292***	5.126***
N=171	(0.16)	(0.36)	(0.47)	(0.63)	(0.80)	(0.42)	(0.55)	(0.70)
Small	2.195***	3.256***	3.741***	4.428***	4.468**	2.869***	3.930***	4.617***
N=47	(0.32)	(0.77)	(1.07)	(1.45)	(1.72)	(0.91)	(1.17)	(1.52)
Medium	1.700***	2.834***	3.547***	4.568***	5.668***	3.017***	4.151***	5.172***
N=56	(0.23)	(0.54)	(0.68)	(0.78)	(0.87)	(0.64)	(0.80)	(0.92)
Large	2.022***	2.716***	3.673***	4.454***	4.650***	3.963***	4.657***	5.439***
N=68	(0.28)	(0.59)	(0.74)	(1.06)	(1.45)	(0.66)	(0.92)	(1.23)

Standard errors in parentheses

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

5.2 Market reactions from insider trading on MERK versus XOSL

This part of the analysis discusses abnormal market reactions across the marketplace on which companies are listed on. We examine both abnormal returns and abnormal turnover for MERK versus XOSL. Based on the findings from subsection 5.1.1, that sales transactions do not seem to yield significant abnormal returns, in addition to there being only five sales transactions on Merkur Market, the results for sales will be less emphasised. Due to the limited sample size on Merkur Market, there will be no discussion of the implications of insider sales on this exchange, nor comparison of sales transactions across the marketplaces. Reference to abnormal market reactions on Merkur Market therefore only refers to purchase transactions. However, sales transactions are included in the tables to check for implications of insider sales transactions on XOSL compared to the full sample.

From Table 6, we see that abnormal returns for MERK are higher than XOSL across all event windows. For example, for event window [-2, 2], MERK CAAR is 6.63 per cent compared to 1.74 per cent for the full sample and 1.40 per cent for XOSL. This represents a difference in average abnormal return of over 5 per cent between the two marketplaces. The abnormal returns for Merkur Market are also almost five times higher than those that Fidrmuc et al. (2006) found for UK firms. The accumulated average abnormal return for MERK versus XOSL from two days before the announcement of inside purchases until three days after is further illustrated in Figure 3.

When discussing the reasoning for the deviations across the marketplaces, we highlight characteristics that can affect abnormal returns that deviate across the marketplaces. Merkur Market aims to enable small and high-growth firms, which characterises the sample firms from this marketplace. The mean market capitalisation of Merkur Market firms is NOK 1.0bn against NOK 14.7bn for XOSL. For Book-to-Market ratios, the values are respectively 0.53 against 0.76. With regard to firm size, Chari et al. (1988) found that for earnings announcements, the excess return on the event day for small firms was 8.25 per cent whilst there were no significant abnormal returns for large firms, indicating that the difference in firm size contributes towards higher abnormal returns on Merkur Market.

For growth characteristics, Aboody and Lev (2000) found firms with high relative R&D expenditure obtain abnormal returns that are twice the size compared with no R&D firms on the event day. This is in line with our findings with abnormal returns on the event day of 2.62 per cent for MERK and 1.08 per cent for XOSL.

Table 6: Price reactions to insider trades according to marketplace

The table show CAARs around the event date for insider trades across the different marketplaces in the sample for buy and sell transactions. The sample includes all reported insider trades on XOSL and MERK from 01.01.2017 to 28.02.2020 above NOK 125,000. Panel A reports CAARs from the aggregated sample separated into buy and sell transactions. Panel B reports CAARs from MERK transactions and Panel C from XOSL transactions. The main event window is [-2, 2] as some insider trades in the sample are reported with a two-day lag. Other event windows are included for robustness. CAARs are measured in arithmetic returns, where the market model has been utilised to calculate β with estimation window [-110, -20]. Insider trades that have the same event time have been aggregated into equally weighted portfolios to eliminate covariance.

	CAAR							
	[0, 0]	[0, 1]	[-1, 1]	[-1, 2]	[-1, 3]	[-2, 0]	[-2, 1]	[-2, 2]
Panel A: Full sample								
Purchases	1.18%***	1.65%***	1.67%***	1.83%***	2.00%***	1.10%***	1.58%***	1.74%***
N=554	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sales	0.09%	0.42%*	-0.52%**	-0.51%**	-0.25%	-0.67%**	-0.34%	-0.33%
N=171	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Panel B: MERK								
Purchases	2.62%***	3.28%***	5.17%***	6.16%***	7.80%***	4.99%***	5.64%***	6.63%***
N=36	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Sales	1.41%	2.05%**	2.59%**	6.55%***	9.35%***	-0.34%	0.31%	0.43%
N=5	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Panel C: XOSL								
Purchases	1.08%***	1.54%***	1.42%***	1.53%***	1.60%***	0.83%***	1.29%***	1.40%***
N=518	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Sales	0.05%	0.37%	-0.62%**	-0.73%**	-0.53%*	-0.68%**	-0.36%	-0.47%*
N=166	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)

Standard errors in parentheses

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

Figure 3: Cumulative average abnormal return across marketplaces, purchase transactions

The figure illustrates average cumulative abnormal arithmetic return for the equally weighed portfolios in the window [-2, 3] for all purchase transactions, sorted by marketplace.

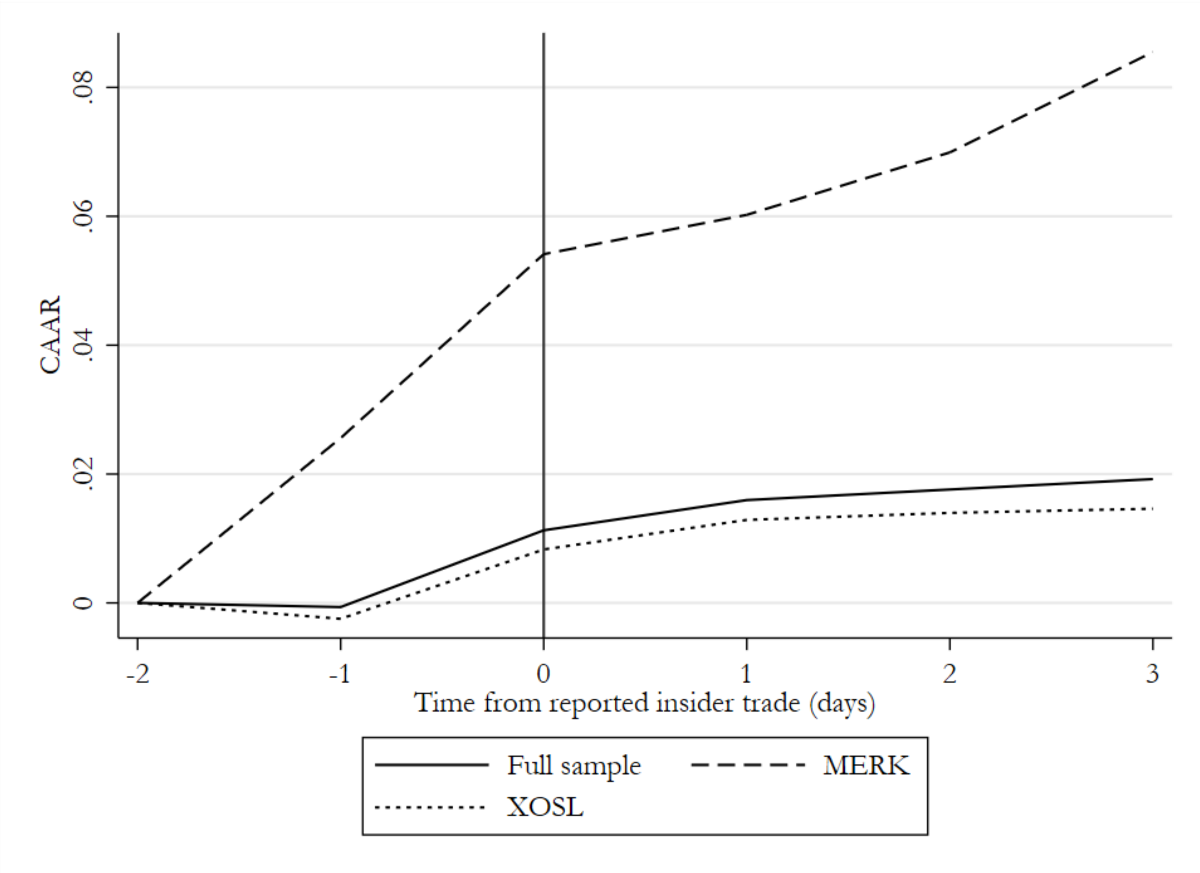


Table 7 shows abnormal turnover for MERK versus XOSL. In line with hypothesis IV, it is apparent that the coefficients for abnormal turnover are also much higher on MERK in comparison with XOSL. Cumulative average abnormal turnover from two days before the announcement of a purchase three days after is further illustrated in Figure 4. For event window [-2, 2] XOSL turnover increase by 5.45 per cent, whilst for MERK the coefficient is 16.50 per cent. Moreover, the market reactions in terms of abnormal turnover for MERK are quite striking where the turnover on the event day increases by 5.12 per cent from the average, which is only marginally smaller than the increase of 5.40 per cent for Moody's ratings from Chae (2005). This is surprising as Moody's ratings are events that contain information that is material to the stock price, in contrast to insider trades.

As it is shown that abnormal trading volume around information generating events increases with higher degrees of information asymmetry (Kyle, 1985), it can be discussed that also the deviations in trading volume between the marketplaces can be explained by characteristics such as size and growth versus value firms.

Table 7: Turnover reactions to insider trades according to marketplace

The table show CAAVs around the event date for insider trades across the different marketplaces in the sample for buy and sell transactions. The sample includes all reported insider trades on XOSL and MERK from 01.01.2017 to 28.02.2020 above NOK 125,000. Panel A reports CAAVs from the aggregated sample separated into buy and sell transactions. Panel B reports CAAVs from MERK transactions and Panel C from XOSL transactions. The main event window is [-2, 2] as some insider trades in the sample are reported with a two-day lag. Other event windows are included for robustness. CAAV is measured using log abnormal turnover, where estimated normal turnover is calculated using the mean adjusted model with estimation window [-40, -11]. The coefficients from the table give the abnormal turnover in reference to the mean. Insider trades that have the same event time have been aggregated into equally weighted portfolios to eliminate covariance between securities.

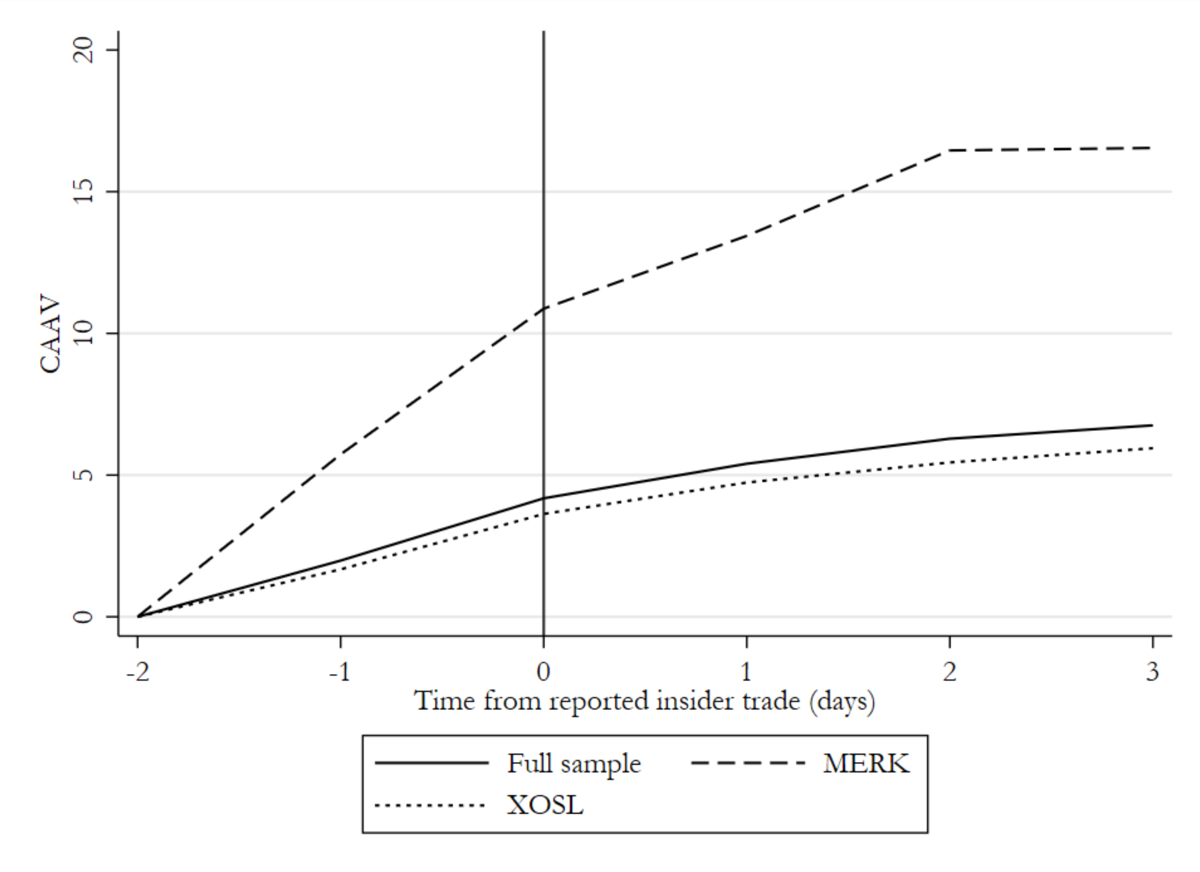
	CAAV							
	[0, 0]	[0, 1]	[-1, 1]	[-1, 2]	[-1, 3]	[-2, 0]	[-2, 1]	[-2, 2]
Panel A: Full sample								
Purchases	2.202***	3.421***	4.569***	5.449***	5.926***	4.191***	5.411***	6.291***
N=565	(0.10)	(0.20)	(0.27)	(0.37)	(0.46)	(0.29)	(0.35)	(0.44)
Sales	1.964***	2.903***	3.650***	4.484***	4.933***	3.353***	4.292***	5.126***
N=171	(0.16)	(0.36)	(0.47)	(0.63)	(0.80)	(0.42)	(0.55)	(0.70)
Panel B: MERK								
Purchases	5.120***	7.672***	10.590***	13.590***	13.670***	10.950***	13.510***	16.500***
N=43	(0.78)	(1.37)	(1.75)	(2.34)	(2.64)	(1.65)	(2.03)	(2.61)
Sales	2.978	5.199	7.119	9.811	14.930	6.353	8.574	11.260
N=5	(2.28)	(4.27)	(6.13)	(8.64)	(10.10)	(5.69)	(7.70)	(10.20)
Panel C: XOSL								
Purchases	1.962***	3.071***	4.073***	4.779***	5.288***	3.634***	4.744***	5.450***
N=522	(0.08)	(0.18)	(0.25)	(0.34)	(0.44)	(0.27)	(0.33)	(0.41)
Sales	1.934***	2.834***	3.546***	4.324***	4.632***	3.262***	4.163***	4.941***
N=166	(0.15)	(0.35)	(0.45)	(0.60)	(0.76)	(0.40)	(0.52)	(0.67)

Standard errors in parentheses

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

Figure 4: Cumulative average abnormal turnover across marketplaces, purchase transactions

The figure illustrates cumulative average abnormal log turnover for the equally weighted portfolios in the window [-2, 3] for all purchase transactions, sorted by marketplace.



Overall, there are large deviations in both CAAR and CAAV for MERK and XOSL firms. We suggest that there are contradicting firm characteristics across the two marketplaces caused by the nature of the marketplaces that can likely explain some of the gap in market reactions. However, we argue that due to fewer regulations and less transparency on Merkur Market, some of the market reaction surplus ex-post insider purchases may be explained by the marketplace on which Oslo Stock Exchange firms choose to list.

5.3 The effect of marketplace on market reactions from insider purchases

In this part, we investigate whether being listed on Merkur Market affects market reactions from insider purchases on the Oslo Stock Exchange. Firstly, we present the cross-sectional regression model for abnormal returns and turnover for the full sample, before regressing on matched XOSL companies in order to see if any causal interpretation is possible. The methodology is explained in Section 4, whilst the approach for creating the matched sample from XOSL (the control group) is elaborated in Section 3. The treatment in the regression model is defined as being listed on Merkur Market. We also include control variables for firm size and Book-to-Market ratio. In addition, we control for turnover in the model for abnormal returns and for absolute returns before the event for the model on abnormal turnover.

The main event window is set to [-2, 2] due to a maximum lag of notification of trade of two days in the sample. We emphasise the results where we adjust for both industry-specific and time-specific fixed effects. Furthermore, standard errors are double clustered on firm and event time. We assume that there will be correlation in the residuals within firms and therefore adjust for this. Furthermore, we also cluster on event week as there are instances of overlapping event windows in the sample.

5.3.1 Market reactions from insider purchases on the Oslo Stock Exchange

Table 8 show regressions for CAR and CAV in event window [-2, 2] for all events in the sample. Full-sample regressions for different model specifications and event windows are found in Table 18, 19, 20 and 21 in the Appendix and are generally in line the findings from Table 8.

Column (1) from Table 8 confirms that abnormal returns from insider trades are significantly higher for MERK companies than XOSL companies with a coefficient of 5.88 per cent. Estimated abnormal returns for XOSL is here 1.17 per cent, which entails a major gap in insider gains for the different marketplaces. When controlling for market capitalisation, Book-to-Market ratio and turnover, the MERK coefficient falls to 5.10. However, this is still both statistically and economically meaningful compared to the average daily return of -0.01 per cent for the full sample. From column (3) we see that also turnover is significantly higher for companies listed on Merkur Market, with an increase in abnormal turnover of 4.88 per cent for companies on this marketplace. However, when including the control variables, the coefficient is lower and no longer statistically significant.

Furthermore, we see that firm size is significantly and negatively correlated with both abnormal returns (Column (2)) and abnormal turnover (Column (4)). This is in line with expectations, confirming the findings of Admati and Pfleiderer (1988), Hong et al. (2000) and Chae (2005). The model estimates that a 1 per cent increase in market capitalisation is followed by a 0.007 per cent decrease in CAR and a 0.704 per cent decrease in CAV. The coefficient for Book-to-Market ratio also has an expected negative sign for both returns and turnover, supporting the findings of Rozeff and Zaman (1998). However, the coefficient is not significant for CAR nor for CAV. Turnover has an unexpected positive sign (Column (2)), although marginal and insignificant. Nor no implications can be drawn from the coefficient for absolute returns ex-ante insider trades (Column (4)), where the standard error is larger than the coefficient.

Overall, we find that abnormal returns and turnover from insider trades are indeed significantly larger on Merkur Market. However, we further find evidence that other variables also correlate with market reactions from the transactions. These are characteristics that deviate largely across the two marketplaces, thereby hindering causal interpretation. In the further, we therefore present regression models on a XOSL sample that match the firm characteristics of the Merkur Market sample to investigate whether causal inference can be made between the marketplace companies are listed on and market reactions from insider trades.

Table 8: Market reactions from insider purchases on the Oslo Stock Exchange

The model is a cross-sectional regression with logarithmic CAR and CAV from insider purchases as the dependent variable. Event window [-2, 2] is applied. The sample consists of all purchase transactions from MERK and XOSL. The CAR is calculated using β from the market model with estimation window [-110, -20]. CAV is measured using log abnormal turnover, where estimated normal turnover is calculated using the mean adjusted model with estimation window [-40, -11]. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to one for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalisation in mNOK. Book-Market is the Book-to-Market ratio. Ln(Turnover) is the logarithmic turnover (volume/mCap). Abs. return [-10, -3] is the difference between absolute return and absolute OSEAX return from t = -10 and t = -3.

	CAR		CAV	
	(1)	(2)	(3)	(4)
	[-2, 2]	[-2, 2]	[-2, 2]	[-2, 2]
MERK	0.0588*	0.0510*	4.883*	3.681
	(0.0301)	(0.0287)	(2.663)	(2.431)
ln(mCap)		-0.00683***		-0.704***
		(0.00194)		(0.261)
Book-Market		-0.00592		-0.0330
		(0.00720)		(0.736)
ln(Turnover)		0.00171		
		(0.00150)		
Abs. return [-10, -3]				1.801
				(5.417)
Constant	0.0117*	0.0822***	3.620***	9.282***
	(0.00605)	(0.0209)	(0.782)	(2.537)
adj. R^2	0.038	0.053	0.081	0.094
SE clustered by firm, week	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
N	1104	1104	1104	1104

5.3.2 The effect of being listed on MERK on abnormal returns from insider purchases

Table 9 reports the regression results for the matched sample with logarithmic CAR as the dependent variable. We observe that the treatment coefficient for Merkur Market is positive and statistically significant across all model specifications. The coefficient from column (4) suggest that insider gains from a purchase increase by 6.63 per cent for event window [-2, 2] given that the company is listed on Merkur Market. The effect of being listed on Merkur Market is reduced to 5.60 per cent when adjusting for firm size, Book-to-Market and turnover. However, the coefficient is significant and represents a substantial potential gain for insiders. The findings from event window [-2, 1] from Table 22 in the Appendix supports these findings, although the results for event window [-1, 2] and [0, 0] give the same implications, but are insignificant. We argue that due to lag in reporting, it is sensible to include the two days before the announcement of the purchase as the sum of the standard deviation and mean in the reporting lag is north of one for Merkur Market (Table 2 and 12). Further, Figure 3 suggest that a large proportion of abnormal returns occur from day -2 to -1, especially for Merkur Market companies.

Table 9: Abnormal returns from insider purchases for MERK and XOSL matched sample

The model is a cross-sectional regression with logarithmic CAR from insider purchases with event window [-2, 2] as the dependent variable. The sample consists of a propensity-score matched sample of MERK and XOSL transactions. The CAR is calculated using β from the market model with estimation window [-110, -20]. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to 1 for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalisation in millions. Book-Market is the Book-to-Market ratio. Ln(Turnover) is the logarithmic turnover (volume/mCap).

	CAR [-2, 2]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MERK	0.0724*	0.0724**	0.0626*	0.0663**	0.0619*	0.0652*	0.0535*	0.0560*
	(0.0381)	(0.0319)	(0.0314)	(0.0325)	(0.0337)	(0.0342)	(0.0306)	(0.0329)
ln(mCap)					-0.00972	-0.00857	-0.0125	-0.0117
					(0.00979)	(0.00934)	(0.00746)	(0.00720)
Book-Market					-0.0458	-0.00860	-0.0189	0.0112
					(0.0344)	(0.0635)	(0.0336)	(0.0491)
ln(Turnover)					-0.000251	-0.0000116	0.00283	0.00259
					(0.00629)	(0.00589)	(0.00609)	(0.00537)
Constant	0.0258*	-0.0240	-0.0158	-0.0317	0.115*	0.0460	0.103*	0.0513
	(0.0151)	(0.0247)	(0.0334)	(0.0358)	(0.0646)	(0.0788)	(0.0550)	(0.0747)
adj. R^2	0.074	0.134	0.152	0.146	0.098	0.087	0.132	0.109
SE clustered by firm, week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
N	52	52	52	52	52	52	52	52

Standard errors in parentheses

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

5.3.3 The effect of being listed on MERK on abnormal turnover from insider purchases

Table 10 shows the regression analysis for event window [-2, 2] with the cumulative abnormal log turnover as the dependent variable. The results suggests that there are significant effects from being listed on Merkur Market on abnormal turnover from insider trades, despite insignificant results from the full-sample regression. From column (8) we find a significant 3.76 per cent increase in turnover from being listed on Merkur Market, thus providing evidence for hypothesis V. Event window [-2, 1] from Table 23 in the Appendix further support these findings with a significant coefficient of 3.47 per cent. It is though clear from Table 23 and 10 that the coefficients for other event windows and model specifications with the exception of column (6) are insignificant.

Table 10: Abnormal turnover from insider purchases for MERK and XOSL matched sample

The model is a cross-sectional regression with logarithmic abnormal turnover from insider purchases as the dependent variable. The sample consists of a propensity-score matched sample of MERK and XOSL transactions. CAV is measured using log abnormal turnover, where estimated normal turnover is calculated using the mean adjusted model with estimation window [-40, -11]. The coefficients from the table give the abnormal turnover in reference to the mean. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to 1 for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalisation in millions. Book-Market is the Book-to-Market ratio. Abs. return [-10, -3] is the difference between average absolute return and average absolute OSEAX return from $t = -10$ and $t = -3$.

	CAV [-2, 2]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MERK	5.419	5.419	4.785	5.106	4.093	3.854*	4.143	3.756*
	(4.246)	(3.670)	(3.620)	(3.532)	(2.702)	(2.227)	(2.611)	(2.237)
ln(mCap)					-0.594	-0.599	-0.737	-0.749
					(1.134)	(1.087)	(1.087)	(1.071)
Book-Market					-4.960*	-3.944	-4.537*	-4.596
					(2.563)	(3.853)	(2.430)	(3.173)
Abs. return [-10, -3]					4.805	7.515	3.426	6.289
					(10.24)	(10.89)	(9.577)	(10.08)
Constant	7.656***	3.421	3.405	1.674	14.53**	13.17*	12.70	12.78*
	(2.488)	(2.062)	(4.022)	(3.426)	(6.830)	(7.517)	(7.601)	(7.282)
adj. R^2	0.040	0.092	0.086	0.087	0.100	0.087	0.099	0.079
SE clustered by firm, week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
N	52	52	52	52	52	52	52	52

Standard errors in parentheses

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

Overall, our results indicate that being listed on Merkur Market yields a surplus in abnormal returns of 5.60 per cent ex-post an insider purchase. Furthermore, we find evidence that turnover increases by 3.76 per cent as a result of being listed on Merkur Market. These are economically significant results and imply that information content is lower on MERK compared to XOSL.

6 Limitations

It is important to highlight that the findings from our analysis should be carefully interpreted on the back of limitations of the study. Firstly, all data collected on insider trades is manually registered by the authors, as there exists no available database of Oslo Stock Exchange NewsWeb notifications. The manual data collection entails risk of human error in the registration of events, as well as misinterpretation of the notifications of insider trades. Despite constructing strict rules before commencing the manual collection of data, there is always a possibility of different interpretation of seemingly similar notifications.

The event study assumptions discussed in Section 4 have some limitations that needs to be adressed. Firstly, the assumption of semi-efficient markets, meaning that share prices consistently reflect all public available information is hard to validate, as for example lag in information flow could deem this condition impossible to fulfill. Second, the condition of event date price only being affected by the event analysed could be flawed. Events could occur simultaneously or be anticipated, leading to biased estimates. Following this, the estimated market reaction to an event could be falsely attributed to the event in question. Furthermore, not aggregating our event portfolios for overlaps regarding all days in the event window could result in a problem of cross-sectional dependence. Constructing aggregated portfolios of trades happening on the same date adjusts for some of this bias, but there is still a possibility of events within the same event window being correlated in the cross-section.

Further, the most distinct limitation is considered to be the size of our data sample. The papers and findings of other authors we reference throughout our thesis provide analyses based on datasets of daily observations spanning over several decades. As Merkur Market opened for trading in 2016, this self-imposed limitation has reduced the possible size of our dataset significantly. In the second part of our analysis, as we perform propensity score matching on two differing groups, and further remove some outliers from Merkur Market, the matched dataset consists of a number of observations on the limit of what is sufficient in order to causally interpret the results. Hence, this fact needs to be considered when analysing our findings.

As being listed on Merkur Market is defined as our treatment in order to enable causal interpretation of our regression analysis, the design of our dataset inables us to match events on MERK and XOSL on pre-treatment characteristics. This imposes a challenge when the conditional independence assumption (CIA) from the propensity score matching methodology is evaluated. As the CIA requires that the outcome variable (CAR or CAV in our case) must be independent of treatment conditional on the propensity score, this assumption is hard to conclude as fulfilled as companies "self-select" themselves to be listed on Merkur Market, and this choice is likely based on the characteristics of the company. Thus, as it is highly possible that the Merkur-listed companies have the returns we observe due to their specific characteristics, which caused them to apply for listing on Merkur Market in the first place, this violation of the CIA is a major limitation to the causal interpretation.

7 Conclusion

This thesis provides an important contribution to the literature on insider trading and its information content on the Oslo Stock Exchange. We investigate market reactions from insider trades on the Oslo Stock Exchange and examine the existence of causal inference between the sub-marketplace companies are listed on and market reactions from insider trades. Merkur Market impose more lax regulations, which we hypothesised increases information imbalance between insiders and outside investors and thereby causes stronger market reactions from insider trades. Several notable conclusions arise from the study.

Firstly, consistent with previous literature from other stock exchanges, we find that insider purchases on the Oslo Stock Exchange yield significant short-term market reactions, both in terms of abnormal returns and turnover. We find market reactions of 1.74 and 6.29 per cent respectively. The implications of insider sales transactions are more ambiguous, suggesting that the information content from sales transactions is lesser. Secondly, both abnormal return and abnormal turnover from insider purchases are significantly higher on MERK compared to XOSL. This is in line with previous findings, that market reactions to information generating announcements are higher in information asymmetry.[11]

Most interestingly, we find that there are surplus market reactions in regard to insider trades from being listed on Merkur Market. Our findings suggest an increase of 5.60 per cent in abnormal returns and 3.76 per cent in abnormal turnover ex-post insider purchases from being listed on MERK. The results are both statistically and economically meaningful and suggest that material information from MERK-listed companies is not disclosed to the same extent as for XOSL listed companies. For those concerned by market inefficiency and its consequences, our results point out that the regulatory framework for Merkur Market seems to increase information asymmetry, which is ultimately hurting outside investors. This again contradicts Oslo Stock Exchange's announced goal for MERK to be an efficient and transparent marketplace. We suggest that regulations for information disclosure should be more equalised across the sub-marketplaces in order to increase market efficiency and enable market prices to better reflect information.

[11] Assuming that information asymmetry is higher for MERK than for XOSL, due to firm characteristics and more lax regulations.

7.1 Suggestions for further research

As highlighted, the emergence of Merkur Market is relatively recent. This limits the number of companies and datapoints in our sample and tampers the possibility for conducting robust studies on the implications of being listed on this marketplace. It is therefore a natural suggestion for further research to conduct our study at a later date when there are more available datapoints. Moreover, there are equivalent sub-marketplaces on other exchanges, such as Nasdaq First North Growth Market, that have longer lifespans and consequently more data. It could be of interest to investigate whether similar effects can be found on such exchanges.

The dataset created for the purpose of this thesis could also be used for further analysis on insider trading on the Oslo Stock Exchange. An interesting approach would be to investigate the profitability aspect of insider trading more thoroughly by conducting a study in line with that of Eckbo and Smith (1998) and examine whether there is a difference in the long-term profitability of insider trading on MERK versus XOSL by constructing portfolios that follow insiders' buy and sell activity across the two marketplaces and compare returns to the benchmark index.

Furthermore, at the time at which this thesis is written, insider trades is the information generating event with the most announcements on Merkur Market. However, as the marketplace matures and the number of listed companies on the exchange increases, it will enable examination of market reactions from other events. We believe it would be interesting to conduct an equivalent study investigating the effect of being listed on Merkur Market on abnormal returns and turnover from events containing information that is material for the stock price. This includes earning announcements, seasoned equity offerings or target and acquisition announcements.

Lastly, we suggest performing the study with high frequency data. This allows for a more fine-tuned analysis of lag in market reaction between the two marketplaces, enabling backtesting of different intraday strategies including shares of differing liquidity. As the traction around Merkur Market has increased dramatically only considering 2020 alone, it could be interesting to assess whether the most liquid stocks listed on MERK still have more significant reactions to market events compared to XOSL-listed companies.

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Appendix

Table 11: Requirements on MERK vs. XOSL

Requirement	MERK	XOSL
Spread of share ownership (proportion of share capital distributed among the general public)	10 per cent	25 per cent
Number of shareholders each holding shares with a value of at least NOK 10,000	No requirement in respect of the number of such shareholders	500
Market capitalisation (in NOK million)	No minimum market capitalisation	300
Operating result must be positive	No	No
History and activity	At least one annual or interim report. Must have commenced planned activities	At least three years history and activity. Exemptions may be granted
Minimum price per share	NOK 1,-	NOK 10,-
Listing prospectus	No duty to prepare a listing prospectus. Must instead publish an admission document in accordance with specific content requirements, which will be inspected and reviewed by the marketplace.	Yes
Financial reporting	IFRS, Norwegian GAAP or other recognised accounting standards	IFRS
Liquidity	No requirement for sufficient liquidity to operate for 12 months	Sufficient liquidity for 12 months
Type of company	Private limited companies, public limited companies and savings banks	Public limited companies and savings banks
Board of directors	At least one board member must have satisfactory expertise in respect of the rules for Merkur Market	All board members must have satisfactory expertise

Information collected from Oslo Stock Exchange (2020b)

A Descriptive statistics

Table 12: Descriptive statistics, exchange type, full data timespan

The table illustrates the mean, median, standard deviation, min and max values of variables market capitalisation (in mNOK), daily traded volume (in thousands), daily volume turnover, book-market-ratio, transaction value (in tNOK), daily arithmetic returns, daily log-returns, log daily Turnover and notification delay (amount of days from transaction to notification on NewsWeb), by exchange in the period 30.06.2016 – 01.04.2020 for Merkur Market (MERK) and Oslo Stock Exchange main market (XOSL).

	Mean	Median	SD	Min	Max .
MERK					
mCap	964	286	1,717	13	10,086
VOL	29.64	1.20	136.78	0.00	3059.80
Turnover	0.00066	0.00005	0.00296	0.00000	0.10640
Book-Market	0.527	0.321	0.574	-1.234	3.385
Transaction value	4,985	800	10,706	137	51,000
Returns (arith.)	0.0007	0.0000	0.0507	-0.3089	0.4814
ln(Returns)	-0.0005	0.0000	0.0498	-0.3694	0.3930
ln(Turnover)	-12.12	-9.97	4.95	-20.96	-3.05
Delay	0.58	0.00	0.72	0.00	2.00
XOSL					
mCap	14,705	2,725	60,952	44	711,802
VOL	481.04	62.10	1435.52	0.00	22382.40
Turnover	0.00222	0.00077	0.00646	0.00000	0.58450
Book-Market	0.756	0.561	0.914	-11.111	8.333
Transaction value	5,329	567	3,0124	125	1,066,646
Returns (arith.)	-0.0001	0.0000	0.0295	-0.1993	0.2407
ln(Returns)	-0.0006	0.0000	0.0294	-0.2223	0.2157
ln(Turnover)	-8.16	-7.17	3.61	-22.73	-2.46
Delay	0.23	0.00	0.44	0.00	2.00
Total					
mCap	14,359	2,628	60,219	13	711,802
VOL	469.68	57.90	1419.27	0.00	22382.40
Turnover	0.00218	0.00074	0.00640	0.00000	0.58450
Book-Market	0.751	0.559	0.908	-11.111	8.333
Transaction value	5,320	569	29,791	125	1,066,646
Returns (arith.)	-0.0001	0.0000	0.0302	-0.3089	0.4814
ln(Returns)	-0.0006	0.0000	0.0301	-0.3694	0.3930
ln(Turnover)	-8.26	-7.20	3.70	-22.73	-2.46
Delay	0.24	0.00	0.45	0.00	2.00

Table 13: Descriptive statistics, transaction type

The table illustrates the mean, median, standard deviation, minimum and maximum values of variables market capitalisation (in mNOK), daily traded volume (in thousands), daily volume turnover, book-market-ratio, transaction value (in tNOK) and notification delay (amount of days from transaction to notification on NewsWeb), for purchase and sales transactions on the full sample, MERK and XOSL.

	Mean	Median	SD	Min	Max
Purchase ($N = 1104$)					
mCap	11,776	2,747	46,993	44	534,686
VOL	929.95	151.85	2424.60	0.00	22382.40
Turnover	0.00448	0.00169	0.01107	0.00000	0.17126
Book-Market	0.799	0.617	0.581	-0.455	4.000
Transaction value	4,437	520	25,153	125	675,000
Delay	0.23	0.00	0.45	0.00	2.00
Sale ($N = 201$)					
mCap	30,802	2,707	117,788	65	711,802
VOL	957.70	230.40	2315.57	0.00	22382.40
Turnover	0.00603	0.00225	0.01330	0.00000	0.10096
Book-Market	0.498	0.375	0.519	-0.490	2.222
Transaction value	15,168	1,104	83,854	126	1,066,646
Delay	0.33	0.00	0.50	0.00	2.00

Table 14: Correlation matrix pre-matching

The table illustrates the correlation matrix of all variables pre-matching (full event sample), in addition to the notification delay.

	MERK	ln(mCap)	mCap	Book-Market	ln(Turnover)	Turnover	Abs. return [-10, -3]	Delay
MERK	1							
ln(mCap)	-0.215***	1						
mCap	-0.0418	0.515***	1					
Book-Market	-0.0908**	-0.0881**	-0.0502	1				
ln(Turnover)	-0.190***	0.0631*	0.0103	0.0364	1			
Turnover	-0.0287	-0.0783**	-0.0423	0.0671*	0.441***	1		
Abs. return [-10, -3]	0.158***	-0.0362	-0.0136	-0.115***	-0.0783**	-0.0237	1	
Delay	0.147***	-0.114***	-0.0516	-0.0114	-0.236***	-0.0951**	0.0337	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 15: Correlation matrix post-matching

The table illustrates the correlation matrix of all variables post-matching, in addition to the notification delay.

	MERK	ln(mCap)	mCap	Book-Market	ln(Turnover)	Turnover	Abs. return [-10, -3]	Delay
MERK	1							
ln(mCap)	-0.290*	1						
mCap	-0.0967	0.716***	1					
Book-Market	-0.0511	0.106	-0.106	1				
ln(Turnover)	0.0311	-0.139	-0.109	0.0465	1			
Turnover	0.0852	-0.239	-0.167	-0.164	0.569***	1		
Abs. return [-10, -3]	0.218	-0.0688	-0.0327	-0.170	0.189	0.251	1	
Delay	0.381**	-0.0811	0.0229	0.0697	-0.0833	-0.0421	0.0387	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Event study with log returns

Table 16: Event study CAAR with log returns

The table reports CAARs for insider purchase and sale transactions around the event date. The sample includes all reported insider trades from 01.01.2017 to 28.02.2020 above NOK 125,000, including both MERK and XOSL. CAARs are measured in logarithmic returns, where the market model has been utilised to calculate β with estimation window [-110, -20]. Insider trades that have the same event time have been aggregated into equally weighted portfolios to eliminate covariance.

	CAAR							
	[0, 0]	[0, 1]	[-1, 1]	[-1, 2]	[-1, 3]	[-2, 0]	[-2, 1]	[-2, 2]
Purchases	1.10%***	1.58%***	1.61%***	1.79%***	1.98%***	0.90%***	1.38%***	1.56%***
N=554	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Sales	0.02%	0.33%	-0.67%***	-0.68%***	-0.47%**	-0.86%***	-0.55%**	-0.56%**
N=171	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)	(0.0026)

Standard errors in parentheses

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

C Cross-sectional regression models

C.1 T-tests of CAR and CAV industry difference

Table 17: Two-sample t-test with equal variances, CAR and CAV by industry

The table presents a two sample t-test comparing the mean of CAR (cumulative abnormal returns) and CAV (cumulative abnormal turnover) in event window [-2, 2] per industry to the mean of all other industries combined for the same event window. The test is performed on the pre-matching full sample of purchase transactions, including insider trades from both MERK and XOSL. The test assumes the two samples to be normally distributed and have the same variance. H0 is that there is no difference in the mean of the two samples.

	Group	Obs.	Mean	Std. err.	Std. dev	95% Conf. Interval		t	Pr(|T| > |t|)	Reject H0
Panel A: CAAR[-2, 2]										
Finance	0	728	.0156634	.0031628	.0853383	.009454	.0218728			
	1	376	.0088604	.0025943	.050306	.0037591	.0139616	1.4232	0.1550	No
Energy	0	905	.0111411	.0024092	.0724779	.0064127	.0158694			
	1	199	.0233758	.0061324	.0865088	.0112825	.0354691	-2.0782	0.0379	Yes
Industrials	0	887	.0148352	.0025705	.0765562	.0097902	.0198802			
	1	217	.0072608	.0047381	.0697959	-.0020779	.0165996	1.3286	0.1843	No
Consumer goods	0	1,001	.0156116	.0023762	.0751789	.0109488	.0202745			
	1	103	-.0086678	.0072224	.0732996	-.0229935	.0056578	3.1282	0.0018	Yes
Healthcare	0	1,057	.0121828	.0022255	.0723535	.007816	.0165497			
	1	47	.0395149	.0179054	.1227532	.0034732	.0755566	-2.4402	0.0148	Yes
Technology	0	942	.0111712	.0023361	.0716992	.0065867	.0157558			
	1	162	.0259948	.0072926	.0928201	.0115933	.0403964	-2.3189	0.0206	Yes
Panel B: CAAV[-2, 2]										
Finance	0	728	5.249788	.3214747	8.673861	4.618658	5.880917			
	1	376	4.183727	.3570759	6.923958	3.481605	4.885849	2.0671	0.0390	Yes
Energy	0	905	5.050703	.2757569	8.295656	4.509504	5.591901			
	1	199	4.140909	.5189125	7.320161	3.117605	5.164214	1.4295	0.1532	No
Industrials	0	887	4.685172	.2704774	8.055506	4.15432	5.216023			
	1	217	5.710506	.5709465	8.410567	4.585166	6.835846	-1.6660	0.0960	Yes
Consumer goods	0	1,001	5.111089	.2555748	8.086025	4.609565	5.612614			
	1	103	2.706083	.8181403	8.303218	1.083305	4.32886	2.8671	0.0042	Yes
Healthcare	0	1,057	4.66931	.2450974	7.968493	4.188377	5.150244			
	1	47	9.775869	1.479128	10.14039	6.798539	12.7532	-4.2443	0.0000	Yes
Technology	0	942	4.643837	.2549806	7.825869	4.143441	5.144234			
	1	162	6.298965	.7570115	9.635184	4.804013	7.793918	-2.3978	0.0167	Yes

C.2 Full sample regression models: CAR

Table 18: Full-sample CAR, different event windows

The model is a cross-sectional regression with logarithmic CAR from insider purchases with different event windows as the dependent variable. CAR is calculated using β from the market model with estimation window [-110, -20]. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to 1 for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalization in millions. Book-Market is the Book-to-Market ratio. Ln(Turnover) is the logarithmic turnover (volume/mCap).

	(1)		(2)		(3)		(4)	
	[-1, 2]		[-2, 1]		[0, 0]		[-2, 2]	
MERK	0.0617*	0.0580*	0.0558**	0.0473*	0.0268	0.0234	0.0588*	0.0510*
	(0.0341)	(0.0346)	(0.0274)	(0.0280)	(0.0190)	(0.0203)	(0.0301)	(0.0287)
ln(mCap)		-0.00627***		-0.00653***		-0.00531***		-0.00683***
		(0.00188)		(0.00179)		(0.00108)		(0.00194)
Book-Market		-0.00508		-0.00745		-0.00669**		-0.00592
		(0.00699)		(0.00660)		(0.00326)		(0.00720)
ln(Turnover)		0.00304*		0.00136		0.00270**		0.00171
		(0.00172)		(0.00158)		(0.00121)		(0.00150)
Constant	0.0122*	0.0866***	0.0122**	0.0791***	0.00629*	0.0718***	0.0117*	0.0822***
	(0.00635)	(0.0207)	(0.00597)	(0.0195)	(0.00364)	(0.0124)	(0.00605)	(0.0209)
adj. R^2	0.042	0.060	0.033	0.048	0.026	0.059	0.038	0.053
SE clustered by firm, week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1104	1104	1104	1104	1104	1104	1104	1104

Standard errors in parentheses

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

Table 19: Full-sample CAR, different model specifications

The model is a cross-sectional regression with logarithmic CAR from insider purchases with event window [-2, 2] as the dependent variable. CAR is calculated using β from the market model with estimation window [-110, -20]. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to 1 for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalization in millions. Book-Market is the Book-to-Market ratio. Ln(Turnover) is the logarithmic turnover (volume/mCap).

	(1) [-2, 2]	(2) [-2, 2]	(3) [-2, 2]	(4) [-2, 2]	(5) [-2, 2]	(6) [-2, 2]	(7) [-2, 2]	(8) [-2, 2]
MERK	0.0627**	0.0582*	0.0631**	0.0588*	0.0525*	0.0503*	0.0529*	0.0510*
	(0.0315)	(0.0299)	(0.0315)	(0.0301)	(0.0283)	(0.0286)	(0.0282)	(0.0287)
ln(mCap)					-0.00752***	-0.00681***	-0.00759***	-0.00683***
					(0.00184)	(0.00194)	(0.00181)	(0.00194)
Book-Market					-0.00338	-0.00624	-0.00316	-0.00592
					(0.00630)	(0.00697)	(0.00652)	(0.00720)
ln(Turnover)					0.00197	0.00149	0.00221	0.00171
					(0.00164)	(0.00149)	(0.00165)	(0.00150)
Constant	0.0111***	0.00747**	0.0144***	0.0117*	0.0866***	0.0774***	0.0917***	0.0822***
	(0.00281)	(0.00325)	(0.00510)	(0.00605)	(0.0210)	(0.0210)	(0.0207)	(0.0209)
adj. R^2	0.023	0.038	0.023	0.038	0.046	0.053	0.046	0.053
SE clustered by firm, week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
N	1104	1104	1104	1104	1104	1104	1104	1104

Standard errors in parentheses

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

C.3 Full sample regression models: CAV

Table 20: Full-sample CAV, different event windows

The model is a cross-sectional regression with logarithmic CAV from insider purchases with different event windows as the dependent variable. CAV is measured using log abnormal turnover, where estimated normal turnover is calculated using the mean adjusted model with estimation window [-40, -11]. The coefficients from the table give the abnormal turnover in reference to the mean. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to 1 for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalisation in millions. Book-Market is the Book-to-Market ratio. Abs. return [-10, -3] is the difference between average absolute return and average absolute OSEAX return from $t = -10$ and $t = -3$.

	(1)		(2)		(3)		(4)	
	[-1, 2]		[-2, 1]		[0, 0]		[-2, 2]	
MERK	3.931	2.535	3.989*	3.171	1.329*	0.917	4.883*	3.681
	(2.483)	(2.129)	(2.172)	(2.030)	(0.693)	(0.631)	(2.663)	(2.431)
ln(mCap)		-0.632***		-0.570***		-0.218***		-0.704***
		(0.217)		(0.221)		(0.0694)		(0.261)
Book-Market		0.0266		0.0864		0.118		-0.0330
		(0.658)		(0.572)		(0.183)		(0.736)
Abs. return [-10, -3]		6.273		-0.349		1.547		1.801
		(5.308)		(3.950)		(1.640)		(5.417)
Constant	3.502***	8.562***	2.948***	7.440***	1.360***	3.025***	3.620***	9.282***
	(0.672)	(2.183)	(0.587)	(2.076)	(0.215)	(0.722)	(0.782)	(2.537)
adj. R^2	0.074	0.095	0.079	0.093	0.082	0.113	0.081	0.094
SE clustered by firm, week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1104	1104	1104	1104	1104	1104	1104	1104

Standard errors in parentheses

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

Table 21: Full-sample CAV, different model specifications

The model is a cross-sectional regression with logarithmic CAV from insider purchases with event window [-2, 2] as the dependent variable. CAV is measured using log abnormal turnover, where estimated normal turnover is calculated using the mean adjusted model with estimation window [-40, -11]. The coefficients from the table give the abnormal turnover in reference to the mean. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to 1 for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalisation in millions. Book-Market is the Book-to-Market ratio. Abs. return [-10, -3] is the difference between average absolute return and average absolute OSEAX return from $t = -10$ and $t = -3$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	[-2, 2]	[-2, 2]	[-2, 2]	[-2, 2]	[-2, 2]	[-2, 2]	[-2, 2]	[-2, 2]
MERK	5.807**	5.473**	5.212*	4.883*	4.131*	4.477*	3.299	3.681
	(2.867)	(2.548)	(2.956)	(2.663)	(2.503)	(2.342)	(2.519)	(2.431)
ln(mCap)					-0.880***	-0.653**	-0.907***	-0.704***
					(0.264)	(0.262)	(0.272)	(0.261)
Book-Market					0.260	0.631	-0.323	-0.0330
					(0.678)	(0.785)	(0.615)	(0.736)
Abs. return [-10, -3]					2.608	1.873	2.676	1.801
					(6.309)	(5.637)	(6.115)	(5.417)
Constant	4.676***	4.053***	4.034***	3.620***	11.51***	8.786***	11.56***	9.282***
	(0.569)	(0.631)	(0.746)	(0.782)	(2.463)	(2.454)	(2.628)	(2.537)
adj. R^2	0.017	0.043	0.056	0.081	0.043	0.057	0.083	0.094
SE clustered by firm, week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	No	No	Yes	Yes
Industry FE	No	Yes	No	Yes	No	Yes	No	Yes
N	1104	1104	1104	1104	1104	1104	1104	1104

Standard errors in parentheses

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

C.4 Matched sample regression models: CAR and CAV

Table 22: Post-match estimation for CAR, different event windows

The model is a cross-sectional regression with logarithmic CAR from insider purchases across different event windows as the dependent variable. The sample consists of a propensity-score matched sample of MERK and XOSL. The CAR is calculated using β from the market model with estimation window [-110, -20]. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to 1 for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalization in millions. Book-Market is the Book-to-Market ratio. Ln(Turnover) is the logarithmic turnover (volume/mCap).

	(1)		(2)		(3)		(4)	
	[-1, 2]		[-2, 1]		[0, 0]		[-2, 2]	
MERK	0.0698	0.0593	0.0682**	0.0605*	0.0323	0.0278	0.0663**	0.0560*
	(0.0451)	(0.0458)	(0.0313)	(0.0335)	(0.0301)	(0.0304)	(0.0325)	(0.0329)
ln(mCap)		-0.0101		-0.00748		-0.00350		-0.0117
		(0.00932)		(0.00598)		(0.00621)		(0.00720)
Book-Market		-0.0196		0.0187		0.00261		0.0112
		(0.0506)		(0.0376)		(0.0221)		(0.0491)
ln(Turnover)		0.00787		0.00559		0.00548		0.00259
		(0.00956)		(0.00677)		(0.00645)		(0.00537)
Constant	-0.00809	0.133	-0.0215	0.0412	0.00499	0.0587	-0.0317	0.0513
	(0.0358)	(0.109)	(0.0365)	(0.0864)	(0.0293)	(0.0880)	(0.0358)	(0.0747)
adj. R^2	0.112	0.085	0.154	0.117	0.070	0.030	0.146	0.109
SE clustered by firm, week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	52	52	52	52	52	52	52	52

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 23: Post-match estimation for CAV, different event windows

The model is a cross-sectional regression with logarithmic CAV from insider purchases with different event windows as the dependent variable. The sample consists of a propensity-score matched sample of MERK and XOSL. CAV is measured using log abnormal turnover, where estimated normal turnover is calculated using the mean adjusted model with estimation window [-40, -11]. The coefficients from the table give the abnormal turnover in reference to the mean. Purchases with values below NOK 125,000 are excluded. MERK is a dummy variable equal to 1 for companies listed on Merkur Market. ln(mCap) is the logarithmic value of market capitalisation in millions. Book-Market is the Book-to-Market ratio. Abs. return [-10, -3] is the difference between average absolute return and average absolute OSEAX return from $t = -10$ and $t = -3$.

	(1)		(2)		(3)		(4)	
	[-1, 2]		[-2, 1]		[0, 0]		[-2, 2]	
MERK	4.445	2.387	4.328	3.474*	1.181	0.790	5.106	3.756*
	(3.203)	(1.615)	(2.864)	(1.965)	(1.110)	(0.767)	(3.532)	(2.237)
ln(mCap)		-0.552		-0.755		0.0752		-0.749
		(0.892)		(0.900)		(0.374)		(1.071)
Book-Market		-2.204		-4.427		-0.204		-4.596
		(2.790)		(2.686)		(1.271)		(3.173)
Abs. return [-10, -3]		13.64		2.039		3.832		6.289
		(8.704)		(7.920)		(3.164)		(10.08)
Constant	4.305*	11.56*	0.184	10.89*	2.352***	2.286	1.674	12.78*
	(2.532)	(6.159)	(3.147)	(5.906)	(0.697)	(2.789)	(3.426)	(7.282)
adj. R^2	0.065	0.137	0.096	0.082	-0.019	0.000	0.087	0.079
SE clustered by firm, week	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	52	52	52	52	52	52	52	52

Standard errors in parentheses

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