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Illegal Insider Trading on Oslo Stock Exchange

An Empirical Investigation

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Abstract

This thesis investigate whether substantial illegal insider trading occurs prior to mergers & acquisitions (M&A) and seasoned equity offerings (SEO) on Oslo Stock Exchange. By examining stock price dynamics prior to the public announcements of these transactions, we investigate whether there are any abnormalities, indicating illegal insider trading. Our initial findings show a significant buildup in cumulative average abnormal return ($\overline{CAR}$) of 4.8 % for the M&A sample. The SEOs are divided by the issuers *ex ante* stated intended use of proceeds, and we find that approximately half of the total buildup in $\overline{CAR}$ occurs prior to the public announcement for recapitalization motivated offerings. Furthermore, we examine whether these findings are a result of illegal insider trading or rumors and market anticipation. We introduce Google search volume as a measure of investor attention. High investor attention suggests a degree of rumors and market anticipation about the upcoming event. We find that the pre-announcement buildup in $\overline{CAR}$ for the M&A sample is mainly driven by rumors about the upcoming event. However, we cannot attribute the same effect to the recapitalization offerings. Finally, we examine whether there are any deal- and firm specific variables that can explain the pre-announcement cumulative abnormal returns (CAR) through a cross-sectional regression analysis. We find that for the M&A sample, Google search volume seems to the most important variable, however for the recapitalization offerings, leverage and profitability appears to explain some of the variation in CAR. Summarized, we find no evidence of illegal insider trading prior to M&A announcements, however our results indicate that there might be some illegal activity prior to recapitalization offerings.

Contents

1 Introduction **1**

2 Literature Review **5**

3 Data **8**
3.1 Sample Selection Criteria . . . 8
3.2 Intended Use of Proceeds . . . 10
3.3 Data Sample . . . 11
3.4 Google Search Volume . . . 13

4 Methodology **15**
4.1 Abnormal Announcement Return . . . 15
4.2 Abnormal Trading Volume . . . 18
4.3 Abnormal Google Search Volume . . . 19
4.4 Cross-sectional Regression . . . 19
4.4.1 Explanatory Variables . . . 20
4.5 Methodology Limitations . . . 22

5 Analysis **23**
5.1 Event Study Results . . . 23
5.2 Abnormal Trading Volume . . . 29
5.3 Abnormal Google Search . . . 32
5.4 Cross-Sectional Analysis . . . 37
5.4.1 M&A Regression Analysis . . . 38
5.4.2 Recapitalisation Regression Analysis . . . 40

6 Conclusion **43**

References **45**

Appendix **48**
A1 Statistical Tests . . . 48
A1.1 Cross-sectional t-test . . . 48
A1.2 Patell test . . . 49
A1.3 Standardized Cross-sectional test (BMP) . . . 50
A1.4 Non-parametric tests . . . 51
A2 Use of proceeds examples . . . 52
A3 Correlation Matrix . . . 53
A4 List of *noisy* observations . . . 54
A5 One-Factor Model Versus Fama-French Three-Factor model . . . 55

List of Figures

1 Number of deals across time and deal type 11
2 Google Trends raw data 14
3 Event Study Timeline 15
4 Development in $\overline{CAR}$ over the Event Window 24
5 $\overline{CAR}$-development for sub-samples excluded *noisy* observation 36

List of Tables

1 Observations split by industry and deal type 12
2 Abnormal and Cumulative Abnormal return, M&A 26
3 Abnormal- and Cumulative Abnormal Returns, SEO 27
4 Abnormal- return and volume, M&A 30
5 Abnormal- return and volume, Recapitalisation 31
6 $\overline{CAR}$ split by Search volume 33
7 $\overline{CAR}$ split by Search volume, ex. *noisy* observations 35
8 Cross-Sectional Regression for *M&A* 39
9 Cross-Sectional Regression for *Recapitalisation* 41
A2.1 Examples of stated intended use of proceeds 52
A3.1 Correlation matrix between explanatory variables, M&A 53
A3.2 Correlation matrix between explanatory variables, *Recapitalisation* 53
A4.1 List of *Noisy* observations 54
A5.1 One-Factor Model vs. Fama-French three Factor 55
A5.2 One-Factor Model vs. Fama-French three Factor 56

1 Introduction

In the Norwegian Security Trading Act from 2007[1], a continuation of the law from 1997, paragraph § 3-3 clearly states that trading on insider information is illegal. In §21-3 it is further specified that violations of Norwegian Security Trading Act § 3-3 can lead to fines and/or prison of up to six years. Nevertheless, there are seen different violations of these laws in the last years. For instance, 18th of September 2013 the Norwegian Supreme Court sentenced a broker firm employee to prison for three years[2]. He possessed case sensitive information that a contract of oil extraction in Iraq was invalid and that DNO would be blacklisted by central authorities in Bagdad. Regardless, he uttered at the table of brokers:

"A good tip, guys: Short DNO. Short DNO now".

The person also recommended one of his customers to short sell the DNO stock, in which the customer immediately shorted 500 000 shares and bought and sold shares in the company for a total of NOK 85 million that day. Professor and scientist in financial crime, Petter Gottschalk, has throughout the years repeatedly claimed that there is a substantial degree of illegal insider trading at Oslo Stock Exchange. When four individuals were accused of illegal insider trading in 2008, Petter Gottschalk further stated: "this is just the tip of the iceberg". After talking to Gottshalk this fall, he argues that there still is a lot of illegal insider trading at the Exchange, as Økokrim[3] does not sufficiently follow up on the issue due to previous failures in court. Also, he mentiones that the exchange does not have sufficient material to provide evidence on illegal insider trading. If Petter Gottschalk is right and there still is a substantial problem, it affects many aspects of trading. For instance Dimitri Vayanos, professor of Finance at London School of Economics, stated in 2004 that given information asymmetry at the exchange, international investors will hesitate to invest at Oslo Stock Exchange. The reduced liquidity further raise the cost of capital for the companies which in turn drives the stock prices down[4]. We believe these implications are severe. There is limited research concerning illegal insider trading from a financial perspective in Norway. We believe the issue of illegal insider trading at the

[1] https://lovdata.no/dokument/LTI/lov/2007-06-29-75
[2] https://www.domstol.no/globalassets/upload/hret/avgjorelser/2013/saknr2013- 821anonymisert.pdf
[3] The central unit for investigation and prosecution of financial crime in Norway
[4] https://www.dagensperspektiv.no/oslo-b%C3%B8rs-blir-ikke-kvitt-innsidestempelet

Oslo Stock Exchange is an important topic, and consequently we will investigate the issue further.

In this thesis we conduct an empirical investigation on the possibility of illegal insider trading activity prior to the public announcement of Mergers & Acqusitions (M&A) and Seasoned Equity Offerings (SEO). To gain insight into the existence of illegal insider trading on Oslo Stock Exchange, we follow the Event-Study methodology, presented by MacKinlay (1997). Using data on 405 successful M&A- and SEO transactions from 2000-2019, we derive the abnormal returns prior to the public announcements of these deals. Following Keown and Pinkerton (1981) we use the cumulative average abnormal returns ($\overline{CAR}$) prior to the public announcements, as a measure of illegal insider trading, before we examine whether there are other factors that can explain the abnormal performance. Consistent with existing literature on foreign markets, we find a significant build-up in average abnormal returns of 4.8 % for M&As, during an event window of 25 days preceding the announcement.

Following Autore et al. (2009) and Silva and Bilinski (2015) we divide the SEO transactions into three categories; *Investments*, *General* and *Recapitalisation*, based on their *ex-ante* stated intended use of proceeds. *Investment* and *General* motivated SEOs experience significant cumulative abnormal returns of 4.0 % and 6.5 % respectively. However, upon disclosure of the deal, the market reacts in the opposite direction. Since previous research find evidence of a negative market reaction to seasoned equity offerings (Masulis and Korwar, 1986), we expect illegal insider traders to short sell rather than to buy the stock. Hence, the potential illegal insider trading does not lead the direction of the abnormal returns and the effect is difficult to isolate. SEOs within the category *Recapitalisation* experience a highly significant cumulative abnormal return of -9.1 % during the event window. This means that approximately half of the total development in $\overline{CAR}$ occurs prior to the announcement.

Some existing literature interpret significant build-up in $\overline{CAR}$ as *de facto* evidence of illegal insider trading (Keown and Pinkerton, 1981). However, this thesis aims to distinguish between actual illegal insider trading and trading based on rumors or market anticipation. The difference between trading based on public and private information can be hard to uncover. Our main challenge is to find a suitable direct measure of investor attention. In previous research, several indirect proxies for investor attention such as trading volume (Gervais et al., 2001; Gao and Oler, 2004) and news media (Jarrell and Paulson, 1989; Jain and Sunderman, 2014) are used. News articles are indirect measures of investor attention as the investor only pays attention to the article if she reads it. In the informational age, most information is only some clicks away. Thus, it is difficult to identify what the investor actually pays attention to. Kahneman (1973) suggested already in 1973 that attention is a scarce resource. Furthermore, Simon (1971) wrote that: "What information consumes is rather obvious: it consumes the attention of its recipients. Hence, a wealth of information creates a poverty of attention and a need to allocate that attention efficiently among the overabundance of information sources...". From a study done by Bohn and Short (2009) at the University of California, they found that the average American in 2008 consumed about 34 gigabytes of data and information each day. This is calculated to an increase of 350 % from 1980 to 2008, which by Herbert Simon's quote should lead to *a poverty of attention.* We thus believe we need to employ a direct measure of attention. Da et al. (2011) argues that Google search volume represents a direct measure. They claim that if an investor searches for a company on Google, he definitely pays attention to it. Da et al. (2011) find that this measure is correlated with, but different than existing proxies of investor attention. In addition, it captures investor attention in a more timely fashion than other proxies. Thus, in this thesis we contribute to the existing literature on illegal insider trading by employing Google search volume as a measure of investor attention. We also include trading volume as a robustness.

When we adjust for abnormal search volume prior to the public announcements of our sample events, we observe that the build-up in $\overline{CAR}$ almost completely disappears in the *M&A* sample. This indicates that the significant pre-announcement $\overline{CAR}$ can be driven by rumors and market anticipation rather than illegal insider trading. However, when applying the same methodology to the recapitalisation motivated SEOs, we find that the build-up in $\overline{CAR}$ prevails. This result suggests that we cannot explain the negative pre-announcement build-up by rumors and market anticipation.

Furthermore, we test the cumulative abnormal return for firms within the *M&A* and *Recapitalisation* category, for other firm- and deal-specific variables. Consistent with our previous findings, we find that Google search volume explains much of the variation in

CAR for the *M&A*s, when we perform a cross-sectional regression analysis. Through the cross-sectional regression analysis for the *Recapitalisation* offerings, however, we find that firm specific variables such as leverage ratio and return on assets, are the most significant factors in explaining the variation in CAR. This result provides less strength to the argument of illegal insider trading in this category.

The remainder of this thesis is structured as follows; In Section 2 we review the existing literature relevant for this topic. Section 3 describes the data and the sample selection criteria. Section 4 presents the methodology used to derive $\overline{CAR}$ and Abnormal Google search, as well as the cross-sectional regression analysis. In Section 5 we present and discuss the empirical results from our analysis. Section 6 concludes the thesis and discuss topics for further research.

2 Literature Review

There has been a number of studies investigating illegal insider trading over the past decades. Most of them indicate that illegal insider trading occurs, and insiders earn abnormal returns prior to relevant public announcements. There is, however, limited research into the illegal insider trading activity on Oslo Stock Exchange (OSE). In addition, this paper utilizes the overflow of information, that the Internet provides, to distinguish between actual illegal insider trading and trading based on rumors and market anticipation.

Analyzing a sample of 194 successfully acquired firms on the New York and American stock exchanges, Keown and Pinkerton (1981) found a substantial buildup in cumulative average abnormal returns prior to merger announcements. Approximately half of the total increase in $\overline{CAR}$ occurs prior to the announcement date, paralleled by a dramatic increase in trading volume. The existence of abnormal returns for target companies prior to public merger announcements are further supported by Sanders and Zdanowicz (1992) and King (2009). Keown and Pinkerton (1981) take these results as *de-facto* evidence of illegal insider trading on the American stock exchanges. Jensen and Ruback (1983) suggest, however, that this run-up simply reflect the market's anticipation of an impending bid. Our paper suggest that there exists a pre-announcement buildup in $\overline{CAR}$ for target firms of M&As on the OSE, consistent with previous research in other countries.

The literature regarding the illegal insider trading activity before public announcements of seasoned equity offerings (SEO) is more limited. However, announcement of an equity offering is empirically correlated with price changes (Lucas and McDonald, 1990); hence insiders have an incentive to trade on their private information. Moreover, Karpoff and Lee (1991) found that an unusual amount of registered insiders sell stock before an announcement of equity offerings, implying that insiders are willing to trade on their superior information prior to common stock offerings. Jung et al. (1996) divides firms based on their investment motives and finds evidence that firms with poor investment motives experience a significant drop in share price after an offerings announcement. Moreover, Autore et al. (2009) divides SEOs based on their stated intended use of proceeds. They find evidence of significant long-run under-performance by issuers that stated debt repayment or general corporate purposes as their intended use of proceeds, while those with investment motives did not experience a significant under-performance. These results are supported in a study by Silva and Bilinski (2015) who finds evidence of a cumulative abnormal return of 2.7 % for issuers stating investment motives in a 5-day event window surrounding the announcement. The cumulative abnormal return in the same event window for issuers stating general corporate purposes and recapitalisation purposes was -3.2 % and -3.3 % respectively. Following these papers, we have classified the SEO by their intended use of proceeds. Similar to Autore et al. (2009), our results provide evidence that offerings motivated by recapitalisation purposes exhibit negative abnormal returns on average in the days prior to the announcement. However, we find a positive pre-announcement cumulative abnormal return for firms stating investment or general corporate purposes as their intended use of proceeds.

One of the main challenges when the stock price exhibits abnormal characteristics prior to an announcement, is to assess whether the abnormal characteristics are a result of market anticipation, other confounding factors or illegal insider trading. Often rumors about an upcoming takeover or SEO arise before the company publicly announce its plans. Hence, some of the cumulative abnormal return that can be observed prior to a public announcement can be attributed to these rumors. Jarrell and Poulsen (1989) argue that much of the trading preceding announcements can be attributed to a well-functioning market rather than illegal insider trading. Their study analyze 172 target firms listed on American stock exchanges. They found that the target firms experienced a significant stock-price runup and surges in volume before the announcements, supporting previous research. However, the presence of rumors in the news media was found to be the strongest variable in explaining unanticipated premiums and pre-announcement runup. Building on the aforementioned research Jain and Sunderman (2014) examined the existence of informed trading in the Indian market from 1996-2010. Adjusting for a significant media speculation variable, they found evidence of illegal insider trading.

In our paper we base the existence of pre-announcement rumors on the Google search volume on the different companies in the sample. Similar to Jarrell and Poulsen (1989), we find that much of the buildup in cumulative abnormal return prior to the announcements can be attributed to market anticipation. When we examine a subsample with the $\overline{CAR}$ of the companies with the least search volume, the runup in $\overline{CAR}$ completely disappears for target firms in a takeover. However, when we look at the buildup prior to SEOs where the stated intended use of proceeds is recapitalization, the $\overline{CAR}$ prevails regardless of search volume, indicating the existence of illegal insider trading.

The use of Google search volume as a measure of market anticipation was first introduced by Da et al. (2011). In their paper they used a sample of 3000 stocks and found that the Google search volume Index (SVI) captured the investor attention in a more timely fashion. They also found that the SVI was correlated but different from existing proxies of investor attention (e.g News Media). These findings are further supported by Fricke et al. (2014) who found that the SVI predicts stock market reactions to earnings announcement. In our initial data on Google Search Volumes we often observe a large spike in searches at the announcement date, which support the findings of Da et al. (2011) and Fricke et al. (2014) that Google search volume capture investor attention in a timely fashion.

Eckbo and Ødegaard (2020) is, to our knowledge, the only other study investigating illegal insider trading on OSE from a financial perspective. Their study analyze insider trades on OSE between 1986-2016, to test for gender-based differences in risk aversion and access to inside information. Using portfolios with weights constructed to reflect insiders' stock-holdings, they find no evidence of abnormal insider performance, suggesting a low degree of illegal insider trading. However, Seyhun (1986) argues that insiders are not expected to trade for their own account prior to possible profitable corporate events. While Eckbo and Ødegaard (2020) argue that insiders does not succeed in "Buying low and selling high", our results indicate that there might be illegal insider trading activity prior to *Recapitalisation* offerings[5]. Following the argument of Seyhun (1986), this might indicate that registered insiders trade through different accounts on OSE, to hide the possible illegal action.

The topic of illegal insider trading is well documented in the previous literature. There is, however, less research regarding both seasoned equity offerings and the Norwegian market. In addition, this paper contributes to the existing literature by adding Google search volume as a measure of rumors and market anticipation. In the following section we describe the data used in the subsequent analysis.

[5]It should be mentioned that Eckbo and Ødegaard (2020) only look at primary insiders such as CEOs and board members. On the other hand, in our definition of insiders we include other stakeholders with insider information such as investment bank employees helping with a transaction.

3 Data

In this section we provide a detailed description of how we obtained our data, as well as descriptive dataset information. We utilize different databases to obtain data throughout the study. To identify mergers and acquisitions we use the *Thomson Reuters SDCPlatinum*^{TM} database, as it is regarded as a highly reliable database on M&A activity (Barnes et al., 2014). Following Hertzel and Li (2010) and Yang et al. (2016) we also apply the SDC database for information concerning the SEOs. Furthermore, we utilize Amadeus 3.0 to collect data from the *Børsprojektet NHH* database to collect firm specific data. Market benchmarks are collected from Ødegaard's website[6] describing asset pricing data on Oslo Stock Exchange. To acquire data on company web search activity we obtain data from the *Google Trends*[7] database.

3.1 Sample Selection Criteria

The initial deal specific information on M&A and equity offerings are obtained from *SDC Platinum*^{TM}. The information include firm- and deal specific information such as market capitalization and announcement dates. We manually obtain data from the financial statements of the firms when there is limited firm-specific data provided by the SDC database. For both the M&A- and the SEO deals we manually cross-check the announcement dates using Newsweb[8]. We also use this cite to obtain information regarding the intended use of proceeds from the offering.

Following Betton et al. (2008) and Bessembinder and Zhang (2013) we impose two filters to the M&As. First, the takeover must be categorized as a merger (M), acquisition of majority interest (AM), acquisition of remaining interest (AR) or acquisition of partial interest (AP). Second, the acquisition must lead to control over the target firm. More specifically this implies that the acquirer owns less than 50 % of the target firm prior to the acquisition and holds more than 50 % post-acquisition. To avoid small deals that are less likely to have material impact on stock returns, we filter out deals were less than 5 %

[6]Bernt Arne Ødegaard - Retrieved from:
http://finance.bi.no/ bernt/financial_data/ose_asset_pricing_data/index.html
[7]Retrieved from: https://trends.google.com
[8]Newsweb is the official source of information on publicly listed companies on Oslo Stock Exchange.

of shares were acquired in the transaction (Bessembinder and Zhang, 2013). Furthermore, we exclude M&A- and SEO transactions based on the following criteria:

1. *Geographic location* – We start by filtering on geographic location. We include only SEOs were the issuing firm is Norwegian. Similarly, the target firm of the M&A transaction is constrained to Norwegian companies only.

2. *Time span* – The period of the analysis is set from 01.01.2000 - 31.12.2019. We choose this period to achieve a balance between robust- and sufficient observations. We exclude earlier observations due to low availability in stock data prior to year 2000.

3. *Public status* – In this paper we utilize data on publicly traded firms in the period prior to M&A- or SEO announcements. We thus remove all M&As and offerings that are not related to an already publicly traded firm. We remove all observations concerning firms that are privately traded, in addition to all initial public offerings (IPO).

4. *Deal size* – Following Bessembinder and Zhang (2013) and Mola and Loughran (2004) we set a minimum deal size on the M&As and SEOs respectively. Bessembinder and Zhang (2013) set a USD 5 million minimum deal restriction on the M&As, while Mola and Loughran (2004) set a USD 25 million restriction on the analyzed SEOs. These are restrictions based on a sample of American firms. The deal sizes in Norway are relatively smaller, and we set the lower deal size restrictions on both M&As and offerings to USD 2 million. We are now left with 273 M&As and 643 offerings.

5. *Merkur Market and Oslo Axess* – We filter out M&As and offerings from firms listed on Merkur Market and Oslo Axess due to limited or insufficient transaction data. 61 M&A observations and 136 equity offerings are removed.

6. *Repair offerings* - When an issuing company contemplate a private placement, they can choose to hold a subsequent repair offering for the existing shareholders that did not participate in the primary offering, to avoid dilution. We do not include these in the sample due to the noise it can create, as the repair offering is often announced together with the original private placement. In addition, the original

offering might bias the estimation window of the repair offering. 84 observations are removed. We are left with 423 seasoned equity offerings.

7. *Inadequate data* - We also exclude deals with missing or uncertain data. Following Keown and Pinkerton (1981), we use 126 trading days prior to the announcement date for each observation in our analysis. There are 50 M&A- and 92 SEO observations with missing price data, and they are thus removed. Finally, the certainty of announcement dates is the foundation of our analysis. In 33 and 48 occasions there are minor uncertainties on the actual announcement days for the M&A- and SEO observations respectively. These observations are thus excluded. Also, following Autore et al. (2009), 7 offerings are excluded due to intended use of proceeds classification ambiguity.

Our main sample consists of 129 M&As and 276 seasoned equity offerings. However, we will add further constraints to the sample as we delve deeper into the analysis.

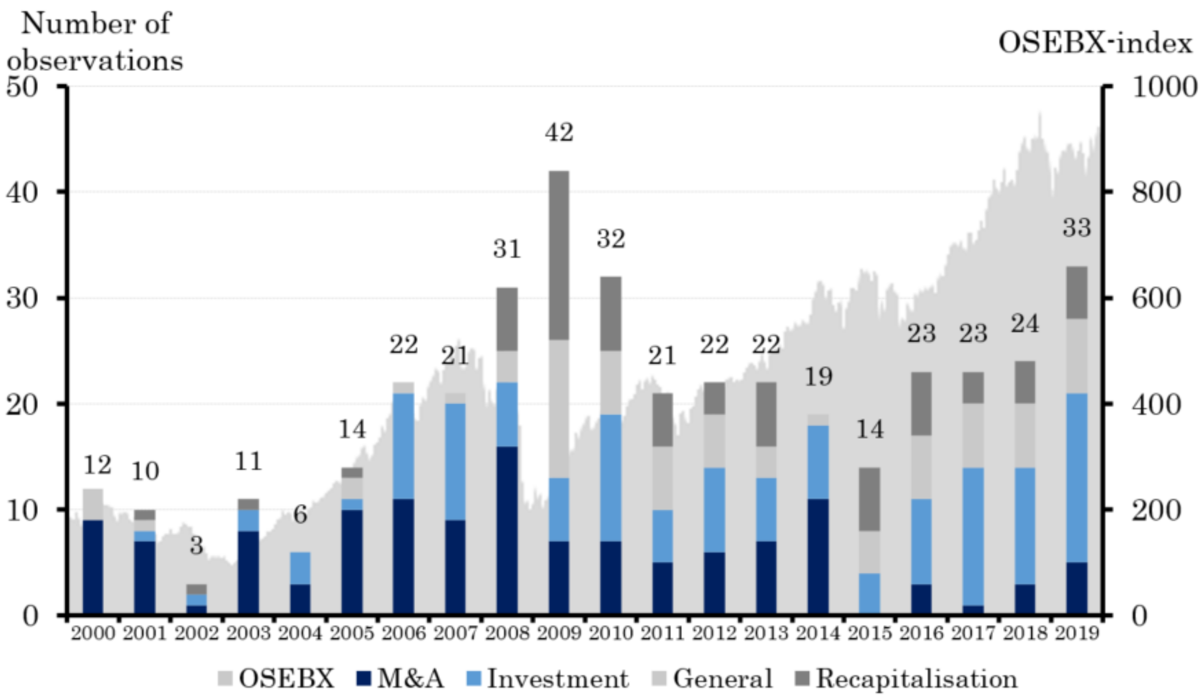
3.2 Intended Use of Proceeds

With our main sample we further divide the different secondary equity offerings into categories given their *ex ante* stated intended use of proceeds, following existing literature (see Autore et al., 2009; Silva and Belinski, 2015). Existing literature split the SEOs into three main categories: *Investment, General* and *Refinancing/Recapitalisation*. The observations that are classified as *Investment* explicitly state in the announcement that the use of proceeds will be used for investment purposes such as acquisitions, operational assets or investments in new projects. The second category, *General*, refers to offerings where the intended use of proceeds is used for general corporate purposes and to improve the working capital position. In the last category, *Recapitalisation*, we include the SEOs where the company needs to restructure and/or pay down existing outstanding debt. Following Autore et al. (2009), we remove observations that both mention investments and repayment of debt to avoid ambiguity. We provide examples of intended use of proceeds classification in Appendix A2.

3.3 Data Sample

Our main sample consists of 129 *M&As*, 131 *Investment* offerings, 74 *General* offerings and 71 *Recapitalisation*. In Figure 1 we present an overview of how our main sample of 405 observations are split across time and deal type. We also include the OSEBX-index over the sample period 2000-2019. From our dataset, we see clear trends in deal types due to different market conditions throughout the years. Prior to the financial crisis in 2008, most of the observations are *M&As* and *Investments*. We consistently observe a peak in *Recapitalisations* in 2009, following the financial crisis.

Figure 1: Number of deals across time and deal type



Note: The chart illustrate the number of observations in the main sample split by deal type and across time (lhs). The main sample is divided into M&As and SEOs. The SEOs are further divided according to the intended use of proceeds into the categories Investment, General and Recapitalisation. We also include the OSEBX-index (rhs) as an indication of the general market condition.

We collected industry specific information from the SDC database on both the M&A targets and the SEOs. The SDC platform divided our dataset into 43 different industry categories. Due to many similar industry categorizations, we manually went through the categories and used the Global Industry Classification Standard (GICS)[9] as a foundation to create an industry composition of 9 industries. An overview of the categorization

[9]Global Industry Classification Standard is a global classification system for listed companies, developed by MSCI and S&P (Oslo Børs, 2020)

across industry and deal type is presented in Table 1. From the table, we can extract that 56 % of the technology deals were *M&As*, while 29 % of the observations from the *Shipping/transportation* industry were *Recapitalisations*. The percentage share of *Recapitalisations* is greatest in the *Real Estate/Property* industry (43 %). However, there are only 14 observations in our sample from this industry. From Table 1, we see that more than half of our 405 deals are in the industries *Oil & Gas*, *Technology* and *Shipping/Transportation*. We include information concerning the dataset across time and industry as we employ these factors as explanatory variables in the cross-sectional analysis in section 5.4.

Table 1: Observations split by industry and deal type

Industry	**M&A**	**Investment**	**General**	**Recapitalisation**	**Total**
Panel A: Number of observations across industry and observation type					
Oil & Gas	14	35	11	14	**74**
Technology	45	21	8	6	**80**
Shipping/Transportation	20	18	4	17	**59**
Consumer Products	18	4	6	5	**33**
Finance & Insurance	7	11	19	4	**41**
Utility & Energy	4	12	4	5	**25**
Healthcare	3	12	11	4	**30**
Real Estate/Property	4	2	2	6	**14**
Other	14	16	9	10	**49**
Total	**129**	**131**	**74**	**71**	**405**
Panel B: % of observations in industry split by deal type					
Oil & Gas	19 %	47 %	15 %	19 %	**100 %**
Technology	56 %	26 %	10 %	8 %	**100 %**
Shipping/Transportation	34 %	31 %	7 %	29 %	**100 %**
Consumer Products	55 %	12 %	18 %	15 %	**100 %**
Finance & Insurance	17 %	27 %	46 %	10 %	**100 %**
Utility & Energy	16 %	48 %	16 %	20 %	**100 %**
Healthcare	10 %	40 %	37 %	13 %	**100 %**
Real Estate/Property	29 %	14 %	14 %	43 %	**100 %**
Other	29 %	33 %	18 %	20 %	**100 %**
Total	**32 %**	**32 %**	**18 %**	**18 %**	**100 %**

Note: In Panel A we present the number of deals across deal type and industry. The main sample is split into the deal type categories M&A, Investment, General and Recapitalisation. We also divide the sample into nine industries based on GICS. In Panel B we provide the deal-type split in to each of the 9 industries.

3.4 Google Search Volume

Based on the results from the first part of our analysis, we find it necessary to collect Google search data on the *M&A*s and the SEOs classified as *Recapitalisation*. We manually obtain the data from the Google Trends website. Google Trends provides a time series index of the search volume for different user queries. It uses a standardized relative scale from 0 to 100, where the period with the most searches take the value 100, a period with half as much searches takes the value 50 and so forth (Choi and Varian, 2012).

The existing literature differ somewhat on how to identify the different companies. Bijl et al. (2016) find that company name search activity is stronger related to stock market returns than ticker searches. Also, when searching for tickers, we experience frequent error messages on our search. These findings combined leads us to search for company name. While searching for a firm, Google Trends often identifies the search term as a company. For instance, if one search for REC Silicon, Google Trends will identify this as a company and filter out searches not related to the firm. We choose this filter were there is adequate data. Regular search term is applied otherwise.

Furthermore, we choose to only include searches that are done in Norway. Preis et al. (2013) find that data filtered according to geographical location is better able to explain stock movements in these locations.

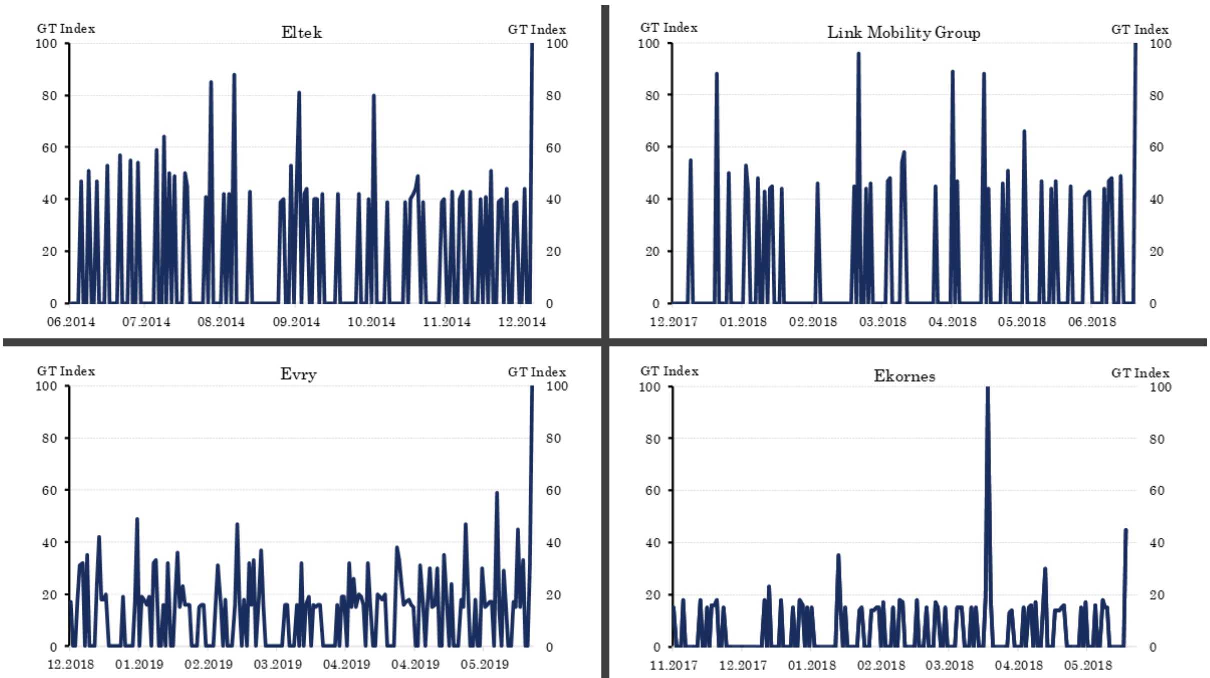
Google Trends provides data in different time intervals. We utilize the customized time-period where we choose data for the trading days period (-126,0). This means that we obtain between 175-195 regular days on each observation. For instance, we collect Google Trends data on REC Silicon from 8th of October 2018 to the announcement 9th of April 2019. We choose this period to be able to compute a normalized- and abnormal search volume for each stock. There is also possible to obtain weekly data for the same period. However, for the precision of the analysis, we do not include this data. The weekly data will create noise as; 1) the week is defined from Sunday to Sunday and 2) and we expect the price run-ups/downs to happen over a limited amount of trading days.

Google Trends provides the opportunity to apply different search filters, such as a *Finance*. Bijl et al. (2016) found that the *Finance* filter does not yield any improvement compared to search for all categories when predicting stock returns. Thus, we do not apply any such filters when retrieving the data.

Finally, we are left with 90 *M&As* and 63 *Recapitalisations* of the total 129 (30.2 % missing values) and 71 (11.3 %) observations respectively. There are a greater number of missing values in the *M&A* sample relative to the *Recapitalisation* sample due to more takeovers in the period were Google Trend data is unobtainable (2000-2003).

Examples of Google Trends raw data on 4 different companies are provided in Figure 2. We include these charts as they provide important insights. We observe that the search volume spikes at the announcement date for the different firms, which we consistently find throughout our sample. This is what we would expect from an accurate measure of investor attention. Although we cannot say that Google Trends is a perfect measure, the data indicates that Google Trends is able to capture investor attention in a timely fashion.

Figure 2: Google Trends raw data



Note: The graphs present examples of daily Google trends raw data for sample firms over the estimation- and event window (-126,0). The Google Search Volume Index is a relative scale stretching from 0-100, where the value 100 is applied to the day with most searches relative to the other observations in the search period. A day with half as much searches takes the value 50 and so forth. Days with close to zero searches relative to the other observations takes the value 0.

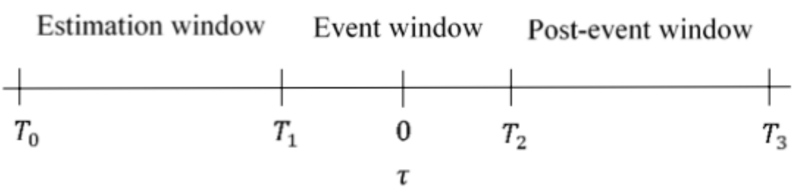
4 Methodology

In this section we describe the methodology we applied to investigate the degree of illegal insider trading on Oslo Stock Exchange prior to M&A- and SEO announcements. In order to measure the effects of these announcements we apply the standard Event Study methodology. Using this methodology, we start by defining the appropriate windows of interest and derive the abnormal announcement return from these.

4.1 Abnormal Announcement Return

An event study is usually used in the literature to measure the impact of an event on the value of the firm (MacKinlay, 1997). The rationale behind such a study is that, given that the semi-strong form of efficient market hypothesis is correct, the effects of an event will immediately be reflected in security prices (Fama, 1970). Following Keown and Pinkerton (1981) we select the date of the public announcement as the event date (t=0) for both M&As and SEOs. Further, daily closing stock prices were collected for 157 trading days surrounding the event date, with 126 trading days before the event and 30 trading days after. Following Keown and Pinkerton (1981) we use an estimation window of 101 trading days (-126,-26) prior to the event window to estimate *normal returns* and use a 27-day event window (-25, 1). To eliminate bias in the estimation of *normal returns* we make sure that the estimation window and the event window does not overlap. This is to prevent event-driven effects from interfering in the calculation of *normal returns* (MacKinlay, 1997). A timeline with the time sequence is illustrated below.

Figure 3: Event Study Timeline



In this study we are interested in the cumulative abnormal return (CAR) over the event window. Following standard event study methodology presented by MacKinlay (1997), we calculate CAR as the cumulative difference between actual returns and estimated *normal returns* (expected return without the event). In order to calculate the *normal return*, we use the one-factor market model. Holler (2012) found this model most accurate when calculating *normal returns.* We use OLS regression to regress excess returns of each sample stock on the excess return of the market. Since the industry composition in our sample reflects the total industry composition on the Oslo Stock Exchange, we use the returns from the *Oslo Børs All-Share Index* (OSEAX) as the market portfolio return.

Estimating normal returns

For each sample security the *normal return* is calculated, where the model´s linear specification follows an assumed joint normality of asset return (MacKinlay, 1997). For each security i we calculate the following:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \epsilon_{it} \tag{1}$$

$$E(\epsilon_{it}) = 0 \text{ and } var(\epsilon_{it}) = \sigma^2_{\epsilon_t}$$

where α_i and β_i are the intercept and slope respectively of the linear relationship between the securities return and the market portfolio return. R_{it} is the actual return in excess of risk-free rate of stock i on day t, and R_{mt} is the return on OSEAX in excess of risk-free rate on day t.

This paper mainly relies on the one-factor model as method for the estimation of "normal returns". However, for robustness we also calculate expected returns were we include two additional factors, using the Fama-French three-factor model (Fama and French, 1993). By applying this model, the "normal returns" are calculated as follows:

$$R_{it} = \alpha_i + \beta_i(MKT_t) + s_i(SMB_t) + h_i(HML_t) + \epsilon_{it} \tag{2}$$

R_{it} is the actual return in excess of the risk-free rate, MKT is the excess return on the Oslo Børs All-Share index, SMB is the average return on a portfolio long small market capitalization securities and short big market capitalization securities. HML is the average return on a portfolio long high book-to-market stocks and short low book-to-market stocks.

Estimating abnormal return

Following Keown and Pinkerton (1981) we use the estimated $\hat{\alpha}_i$ and $\hat{\beta}_i$ to calculate the abnormal returns for each security within the event window (-25,1). The abnormal returns for each security are given by:

$$AR_{i\tau} = R_{i\tau} - \hat{\alpha}_i - \hat{\beta}_i R_{m\tau} \tag{3}$$

where $\hat{\alpha}_i$ and $\hat{\beta}_i$ are the ordinary least squares estimates of α_i and β_i.

Cumulative abnormal return (CAR)

In order to draw overall inference for the events, the abnormal return needs to be aggregated. The cumulative abnormal return is calculated by aggregating the abnormal returns of the individual stock through time. We thus accommodate a multiple period event window from τ_1 to τ_2.

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \tag{4}$$

Average abnormal return ($\overline{AR}$)

The abnormal return for each observation are averaged across observations at each period t. Given N observations, the sample average abnormal return is calculated as:

$$\overline{AR}_\tau = \frac{1}{N} \sum_{i=\tau}^{N} AR_{i\tau} \tag{5}$$

Cumulative average abnormal return ($\overline{CAR}$)

The average abnormal returns from the equation above is then aggregated over the event period in order to calculate the $\overline{CAR}$.

$$\overline{CAR_i}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} \overline{AR}_\tau \tag{6}$$

Statistical tests are further conducted in order to determine if the abnormal and cumulative abnormal returns prior to the announcement are equal to zero. We have utilized a variety of both parametric and non-parametric tests to examine whether this hypothesis is true.

A description of these tests follows in Appendix A1.

4.2 Abnormal Trading Volume

In this study we utilize the abnormal trading volume prior to the announcement of an M&A or SEO. The methodology behind the estimation of abnormal trading volume follows the same event study methodology described in Section 4.1. In this paper, trading volume is measured as the percentage of outstanding shares traded on a given day. Previous research suggest that raw trading volume is highly non-normal, but that a log-transformation yields measures that are approximately normally distributed (Ajinkya and Jain, 1989). Hence, we calculate the trading volume for security i at time t ($V_{i,t}$) as follows:

$$V_{i,t} = \ln(\frac{n_{i,t}}{S_{i,t}} * 100) \tag{7}$$

where $n_{i,t}$ denotes the number of shares traded on day t and $S_{i,t}$ the number of shares outstanding for security i on day t. In order to calculate the abnormal trading volume preceding the announcements we applied a mean-adjusted model. The expected trading volume is calculated as the mean trading volume over the estimation window. The model can be written as follows:

$$AV_{i,t} = V_{i,t} - \overline{V_{i,t}} \tag{8}$$

where, AV_{it} is the abnormal trading volume for security i at day t, and:

$$\overline{V_{i,t}} = \frac{1}{T} \sum_{T=t_0}^{T_1} V_{i,t} \tag{9}$$

In the equation above T denotes the number of days in the estimation period, which is the same as for abnormal returns, 101 days.

4.3 Abnormal Google Search Volume

To distinguish between market anticipation and actual illegal insider trading this paper applies data from Google Trends as a measure of investor attention. We investigate whether there is any abnormal search volume in the days preceding a public announcement. Abnormal search volumes in the days prior to an announcement suggest that there is leakage of rumors about the upcoming event, hence justifies a possible price runup. To estimate the expected search volume and subsequent abnormal search volume, this study relies on a mean-adjusted model. Following Bijl et al. (2016) and Da et al. (2011), we calculate the abnormal search volume as follows:

$$ASVI_{i,t} = SVI_{i,t} - \overline{SVI_{i,t}} \tag{10}$$

where, $SVI_{i,t}$ is the Google search volume for security i at day t, $ASVI_{it}$ is the abnormal Google search volume for security i at day t, and:

$$\overline{SVI_{i,t}} = \frac{1}{T} \sum_{T=t_0}^{T_1} SVI_{i,t} \tag{11}$$

T denotes the number of days in the estimation window, which remains the same as for abnormal returns and abnormal volume, 101 days.

After the computation of abnormal search volume for each security within the event window, we calculate the average abnormal search volume for each security. We further distinguish between high- and low search firms, separated on the median observation.

4.4 Cross-sectional Regression

Based on the initial findings, we perform a cross-sectional regression analysis on the *M&A*- and *Recapitalisation* samples. We use ordinary least squares (OLS) for coefficient estimates to our variables described in the subsequent subsection. Following MacKinlay (1997) we perform the regression:

$$CAR_i = \delta_0 + \delta_{1x,1i} + ... + \delta Mx, Mi + \epsilon_i \tag{12}$$

given the sample of N observations and M features, where CAR_i is the cumulative abnormal return of the i^{th} observation. The δs are the coefficient of the variables, while the ϵ_i is the error term, which is assumed to be uncorrelated with the variable and to have a mean of zero. MacKinlay (1997) reasons that heteroscedastic standard errors are expected when an event study is conducted. We provide heteroscedasticity-consistent standard errors, following the approach of White (1980).

4.4.1 Explanatory Variables

We include different explanatory variables in our cross-sectional analysis. This section seeks to address the rationale behind the inclusion of some of the variables. We examine previous empirical research on the topics M&A and SEO to obtain relevant explanatory variables for our cross-sectional analysis. The main ambition for the cross-sectional analysis on our *M&A* sample is to investigate if the Google Search Binary variable *High ASVI* remains significant when including other explanatory variables. In our *Recapitalisation* cross-sectional regression analysis, more attention is directed to other factors that might explain the plunge in $\overline{CAR}$ prior to the offering announcements.

Google Trends ASVI is the main indicator variable we want to research further in the *M&A* regressions. In section 5.3 we elaborate on why Google search volume can be a useful, direct measure of investor attention.

In our *Recapitalisation*-regressions we examine whether the type of *flotation method* can explain some of the negative development in $\overline{CAR}$ prior to the announcement dates. Both Eckbo et al. (2007) and Bortolotti et al. (2008) find that *Private Placements* on average offer higher returns than other flotation methods (i.e. *Rights issues*) at announcement.

Moreover, we control for deal specific variables such as *Number of Bidders*, *Acquirer nation* and *Relative Deal Size*. The reasoning behind the inclusion of the former, is that different bids can potentially lead to more news prior to the announcement. It is important to notice that the Google Trends variable and number of bidders both potentially address rumor effects. This can cause multicollinarity to the model. However, as the correlation between the two variables are low (0.043, see Appendix A3), we include both. We also include the binary variable *Acquirer nation* to investigate whether a foreign acquirer has any implications on the pre-announcement $\overline{CAR}$. We further include a variable for

Relative Deal Size, as the adverse selection model suggest that larger equity offerings are associated with unfavourable market reactions.

We also add the natural logarithm of the market capitalization of the firm as an explanatory variable in both the *M&A* (target firm)- and *Recapitalisation* regressions. We believe this is an important variable to include, as it describes the size of the firm (measured in valuation metric). We have calculated the abnormal returns based on the market model, and therefore we want to adjust for the additional risk of smaller firms and corresponding higher expected returns (Fama and French, 1993).

We include the book-to-market ratio *(B2M)* as an indicator variable identifying the valuation prospects of the target firm in the *M&A* sample and the issuing firm in the *Recapitalisation* sample. With rational pricing, high book-to-market signals persistent poor earnings while a low book-to-market ratio indicate strong earnings (Fama and French, 1995). As we employ the market model to calculate abnormal returns, we include the book-to-market ratio to adjust for the findings of Fama and French (1995). The book-to-market ratio is retrieved from the SDC-platform and based on Last Twelve Months (LTM) book values and market value prior to announcement date.

We include an explanation variable for how levered each firm is. The ratio is based on total debt divided by total assets. The numbers are gathered from both the SDC database and financial statements from last fiscal year prior to announcement.

$$Leverage = \frac{TotalDebt}{TotalAssets} \tag{13}$$

We believe this variable is especially interesting in the cross-sectional regression on the recapitalisation sample as one might suspect the negative development in $\overline{CAR}$ prior to the announcement to be caused by investors anticipating that a subsequent offering is inevitable.

Another interesting explanatory variable that we include, is the pre-announcement return on assets ROA. The financial ratio is a measure of profitability, and is defined as:

$$ROA = \frac{NetIncome}{TotalAssets} \tag{14}$$

We include the ratio as an explanatory variable to investigate if the buildup in $\overline{CAR}$ can be explained by the profitability of the firm.

4.5 Methodology Limitations

The event-study methodology can be useful in several ways, when assessing the impact of an event on the valuation of a firm. However, the methodology rely on assumptions that may not hold in all circumstances. We will in this section briefly discuss some of the limitations of the event study methodology.

Firstly, the choice of model to estimate expected returns may have a bearing impact on the significance and magnitude of our results. In order to test the robustness of abnormal returns, we estimate normal returns using multiple estimation models.

Secondly, in accordance with MacKinlay (1997) we experience increasing variance when testing our null hypothesis that $\overline{CAR}$ equals zero. Boehmer et al. (1991) argue that the null-hypothesis is wrongly rejected too often, due to the event induced variance. To adjust for this issue, we apply the standardized cross-sectional test introduced by Boehmer et al. (1991).

Finally, when we analyze the aggregated abnormal returns, we assume that the abnormal returns of the different securities are independent. However, overlap in the event window in calendar time, introduce a problem of cross sectional dependence. This means that the covariance between the abnormal returns of the different securities are different from zero (MacKinlay, 1997). MacKinlay (1997) suggests different accommodations to deal with the clustering problem. We use one of these accommodations, namely to aggregate the abnormal returns into a portfolio, dated using event time. Also, we perform the test introduced by Boehmer et al. (1991). They conclude, from their simulations, that the results of their standardized cross-sectional test are essentially unaffected by the presence of event-date clustering (Boehmer et al., 1991).

In the subsequent section we apply the methodology, described in this section, on the sample data. Furthermore, we present the results from our analysis and discuss these in the context of economically relevant theories.

5 Analysis

In this section, we report the results from our analysis of illegal insider trading on Oslo Stock Exchange. First, we show that there is a significant buildup in $\overline{CAR}$ prior to M&A- and SEO announcements in our sample. Second, we distinguish between buildup driven by possible illegal insider trading and buildup in $\overline{CAR}$ that can be explained by rumors about an upcoming event. Finally, we perform a cross-sectional regression analysis to examine whether firm- and deal specific variables can explain the variation in CAR.

5.1 Event Study Results

The common method for assessing illegal insider trading in the existing literature, is to calculate the buildup in $\overline{CAR}$ in the days prior to a public announcement (see Keown and Pinkerton, 1981; Sanders and Zdanowic, 1992). This gives us the following hypothesis:

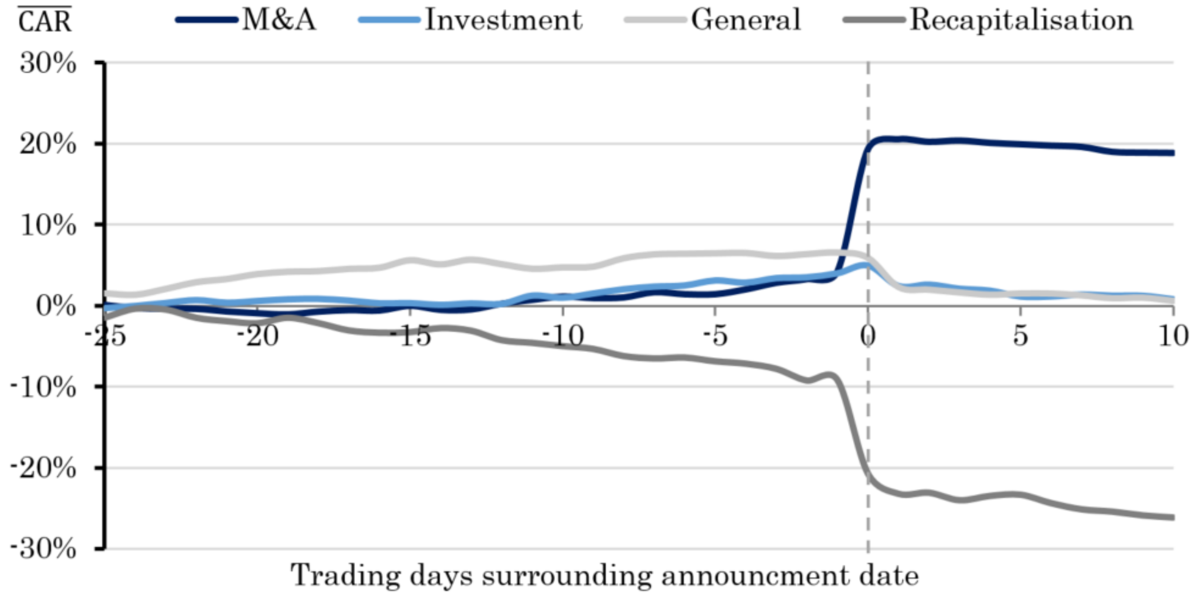
$$H_0 : \overline{CAR} = 0$$

$$H_A : \overline{CAR} \neq 0$$

To test this hypothesis, we applied the event study methodology described in the previous section. When calculating the $\overline{CAR}$, we distinguish between M&As and the three SEO classifications. The rationale behind the division of the SEOs is that previous literature (e.g Walker and Yost, 2008; Silva and Belinski, 2015) finds that the market tends to react differently upon the announcement of these. Thus, to identify any illegal insider trading we find it necessary to look at the different SEO categories in isolation.

In Figure 4 we present the cumulative average abnormal returns for each category. Consistent with previous literature on agency issues and asymmetric information (Walker and Yost, 2008), the issuers of SEOs experience negative abnormal returns on average surrounding the public announcement. The target firms of M&As experience positive abnormal returns surrounding the announcement date. This is also consistent with previous M&A research (Keown and Pinkerton, 1981; Sanders and Zdanowicz, 1992).

Figure 4: Development in $\overline{CAR}$ over the Event Window



Note: The chart present the cumulative average abnormal returns per deal-type in the window [-25,10]. The four deal-types are M&A and the three SEO-categories Investment, General and Recapitalisation. The abnormal returns are calculated using the one-factor market model. The alpha and betas are estimated over 101 trading days in the window [-126,-26]. Stock prices are collected from Børsprosjektet NHH, where we gather the prices adjusted for corporate events such as dividends and splits.

There seems to be a clear distinction between the different categories as target firms of *M&A* transactions experience positive abnormal returns on average, whereas issuers stating *Recapitalisation* motives experience negative abnormal returns both prior and after the public announcement. We observe that the buildup in $\overline{CAR}$ begins thirteen days prior to the announcement for *M&A*, while the development for *Recapitalisation* starts at the beginning of the event window, 24 trading days prior. The buildup in $\overline{CAR}$ we observe from the *Recapitalisation* sample can also be caused by other factors than illegal insider trading. It is reasonable that the stock performance of a firm right before a restructuring/recapitalisation is worse the last 25 trading days prior to the announcement, than in the estimation window. This issue will be investigated further in the analysis.

Issuers stating *Investment* or *General* motives experience on average positive abnormal returns prior to the public announcement. However, the abnormal returns shift to negative upon the public announcement. Earlier research on *Investment* and *General* offerings, suggests that the market will, on average, have a negative reaction to the announcement. We thus expect an illegal insider trader to short sell the stock rather than to buy it. As we observe positive abnormal returns prior to the announcement of these types of offerings, the illegal insider trading (if any) does not lead the direction of the abnormal return. Hence, it is difficult to isolate the possible illegal insider trading. The combination of a positive buildup in $\overline{CAR}$ prior to the announcement and a subsequent decrease at the announcement could also indicate a level of market timing, where managers of issuing firms exploit overvalued equity (Loughran and Ritter, 1995).

Another argument that substantiates the conclusion of lesser illegal insider trading in the *Investment* and *General* offerings, is the risk versus reward aspect from the perspective of the illegal insider trader. Consistent with previous literature (see Keown and Pinkerton, 1981; Walker and Yost, 2008), our findings suggests that there are possible financial gains from buying before *M&A* announcements ($|\overline{AR}|$ is equal to 15.1 % at announcement day) and short selling before *Recapitalisation* announcements (11.5 %). However, the possible gains from short selling before *Investment* (1.0 %) and *General* offering announcements (0.6 %) is substantially smaller. Thus, the reward for illegal insider traders to invest and short sell before *M&A*- and *Recapitalisation* announcements, respectively, is far greater than to short sell before the other offering announcements. Meanwhile, the risk an illegal insider trader is exposed to, following the criminal offense, is more stable for the different deal categories[10]. According to economic theory a rational decision-maker is indifferent of two options where the expected return is the same. However, if an alternative is riskier than the other and the expected return is still the same, most people prefer the less riskier alternative (Tversky and Kahneman, 1981). If the illegal insider trader can be considered as a rational decision-maker, the person would prefer to go long before an *M&A* or short a *Recapitalisation* offering. Based on these results, the rest of the paper mainly focus on *Recapitalisation* and *M&A*, as the potential for illegal insider trading seems to be greater in these categories.

[10] According to Norwegian legislative history (i.e. the *Sense*-sentence from 2011) there are other aspects than possible percentage gain from the illegal insider trade that are more decisive for the sentencing. For instance, the official position of the offender, level of breach in trust and degree of impulsiveness are some important criteria.

Table 2: Abnormal and Cumulative Abnormal return, M&A

		M&A										
N	Day						$\overline{CAR}$ Window					
		Abnormal Average Returns						**Cumulative Abnormal returns**				
		$\overline{AR}$ %	**t-test**	**Patell Z**	**BMP**	**Wilcox.**		$\overline{CAR}$ %	**t-test**	**Patell Z**	**BMP**	**Wilcox.**
129	**-13**	0.05	0.13	0.35	0.28	0.40	**[-13,-13]**	0.05	0.13	0.35	-0.13	0.40
129	**-12**	0.72	1.84***	3.01***	2.07**	0.71	**[-13,-12]**	0.76	1.45	2.38***	0.40	0.96
129	**-11**	0.47	1.35	1.14	0.73	0.70	**[-13,-11]**	1.23	2.18**	2.60***	0.58	1.38
129	**-10**	0.40	1.21	1.60	1.38	0.52	**[-13,-10]**	1.63	2.65***	3.05***	0.85	1.73*
129	**-9**	−0.18	−0.62	−1.45	−1.26	−1.33	**[-13,-9]**	1.45	2.18**	2.08**	0.58	1.19
129	**-8**	0.08	0.28	0.50	0.48	−0.25	**[-13,-8]**	1.53	1.91*	2.10**	0.62	1.03
129	**-7**	0.64	1.83*	2.35**	1.88*	0.82	**[-13,-7]**	2.17	2.39***	2.83***	0.99	1.50
129	**-6**	−0.24	−0.78	−1.21	−0.90	−0.39	**[-13,-6]**	1.93	2.02**	2.23**	0.77	1.23
129	**-5**	0.00	0.00	1.39	1.41	0.39	**[-13,-5]**	1.93	2.06**	2.56***	0.99	1.28
129	**-4**	0.59	1.97*	2.54***	1.89**	0.85	**[-13,-4]**	2.52	2.55***	3.23***	1.35	1.60
129	**-3**	0.82	2.40***	2.22**	1.90*	0.92	**[-13,-3]**	3.34	3.24***	3.75***	1.69*	2.08**
129	**-2**	0.46	1.60	1.82*	1.70*	1.00	**[-13,-2]**	3.80	3.52***	4.12***	1.96*	2.29**
129	**-1**	0.94	3.03***	3.51***	2.84***	2.02**	**[-13,-1]**	4.74	4.10***	4.93***	2.43***	2.52***
129	**0**	15.10	7.60***	67.02***	8.70***	6.01***	**[-13,0]**	19.84	11.52***	22.66***	8.93***	6.41***
129	**1**	1.23	2.88***	4.75***	2.84***	1.73*	**[-13,1]**	21.07	12.33***	23.12***	9.49***	6.55***

Note: The table presents the abnormal- and cumulative average abnormal returns for the 129 M&A observations from 13 trading days prior to the announcement to 1 trading day post-announcement [-13,1]. We include a t-test, Patell Z test, BMP test and Wilcoxon rank test for both the abnormal- and cumulative average abnormal returns to investigate whether the different returns are equal to zero. *, ** and *** denote test-statistics significant at 10 %, 5 % and 1 %, respectively. Please see Appendix A1 for calculation of the different test-statistics.

As we see from Table 2, the $\overline{CAR}$ for *M&A* starts to take on abnormal characteristics in the days before the official public announcement. Furthermore, we observe a large spike in the average abnormal return of 15.10 % on day 0, suggesting that the announcement generally came as a surprise to the market. The cumulative average abnormal return for the M&As becomes positive 12 days prior to the announcement. In addition, the daily average abnormal return is positive in 11 out of 13 days prior to the announcement. From the different tests presented in Table 2, we extract that for both the t-test and the Patell Z-test, the $\overline{CAR}$ is significantly different from zero in the 11 and 12 days prior to the announcement, while from the BMP- and the Wilcoxon rank sum test we observe that the last three days is significantly different from zero. The BMP-test is robust to the variance induced by the event, and explains the difference in significance between the tests. The significant pre-announcement buildup in $\overline{CAR}$ gives us reason to believe that there might exist illegal insider trading. However, compared to existing literature on illegal insider trading upon merger announcements, the buildup in $\overline{CAR}$ of 4.74 % is relatively small.

Keown and Pinkerton (1981) and King (2009) found that approximately half and 39 % of the build up in $\overline{CAR}$ occurs prior to the announcement date respectively, we find this number to be 24 %.

Overall, our results from the M&A sample indicate that there might exist trading based on private information as some of the previous literature on M&As (see Keown and Pinkerton, 1981) has interpreted significant pre-announcement buildup in $\overline{CAR}$ as *prima facie* evidence of illegal insider trading. However, there may be other explanations for why the returns take on abnormal characteristics prior to the announcement, which will be discussed in the subsequent sections.

Table 3: Abnormal- and Cumulative Abnormal Returns, SEO

Panel A: Abnormal Returns

Day	**Investment N=131**					**General N=74**					**Recapitalisation N=71**				
	$\overline{AR}$ (%)	**t-test**	**Patell Z**	**BMP**	**Wilcox.**	$\overline{AR}$ (%)	**t-test**	**Patell Z**	**BMP**	**Wilcox.**	$\overline{AR}$ (%)	**t-test**	**Patell Z**	**BMP**	**Wilcox.**
-25	−0.28	−0.92	0.03	0.03	−0.40	1.55	1.58	2.26**	1.17	0.43	−1.43	−1.62	−2.63***	−2.21**	−1.14
-24	0.27	0.82	0.29	0.27	−0.65	−0.17	−0.30	−0.46	−0.35	−0.21	1.10	1.49	2.09**	1.53	0.74
-23	0.36	1.27	0.77	0.75	−0.21	0.72	1.15	0.89	0.85	0.21	−0.11	−0.23	−0.36	−0.42	−0.15
-22	0.36	1.23	1.54	1.33	0.32	0.82	1.81*	1.92*	2.17**	1.34	−1.02	−1.54	−2.23**	−1.99*	−1.30
-21	−0.32	−1.32	−1.10	−1.26	−1.08	0.39	0.85	0.30	0.34	−0.14	−0.41	−0.77	−1.04	−1.06	−0.15
-20	0.21	0.94	0.86	0.96	0.26	0.60	1.09	2.31**	1.41	0.59	−0.25	−0.33	−0.49	−0.39	−0.46
-19	0.21	0.91	0.62	0.75	0.70	0.28	0.73	−0.07	−0.08	−0.26	0.67	0.92	1.40	1.10	0.63
-18	0.05	0.17	0.48	0.44	0.16	0.07	0.17	−0.51	−0.37	0.49	−0.67	−0.66	−0.92	−0.72	0.52
-17	−0.21	−0.78	−0.53	−0.54	−0.46	0.28	0.75	0.92	1.11	0.55	−0.90	−1.05	−2.38***	−1.08	−0.74
-16	−0.33	−1.00	−0.75	−0.65	−0.33	0.14	0.27	−0.45	−0.28	0.74	−0.28	−0.45	−0.10	−0.09	−0.14
-15	0.02	0.05	0.08	0.08	−0.52	0.91	1.80*	1.20	1.18	0.54	0.07	0.12	−0.18	−0.17	0.67
-14	−0.22	−0.74	−0.80	−0.78	−0.27	−0.51	−1.35	−1.32	−1.67*	−1.38	0.50	0.48	0.53	0.46	−0.22
-13	0.18	0.51	0.33	0.30	−0.78	0.58	1.25	1.06	1.06	1.30	−0.32	−0.32	−0.34	−0.18	−1.01
-12	−0.06	−0.15	0.79	0.45	0.14	−0.55	−1.44	−0.84	−0.65	−1.43	−1.16	−1.48	−1.62	−1.25	−0.66
-11	1.02	2.27**	3.20***	2.26**	1.02	−0.56	−1.39	−1.35	−1.34	−1.38	−0.33	−0.37	−1.45	−0.84	−0.22
-10	−0.26	−0.53	−1.88*	−1.28	−1.37	0.17	0.52	0.58	0.74	0.44	−0.40	−0.66	−1.46	−1.26	−0.84
-9	0.52	1.81*	2.53***	2.39***	1.31	0.08	0.20	−0.33	−0.32	−0.44	−0.35	−0.70	−0.73	−0.72	−0.40
-8	0.53	1.03	0.94	0.71	−0.01	1.03	1.91*	2.08**	1.91*	1.32	−0.88	−1.21	−1.97*	−1.38	−0.94
-7	0.32	0.70	2.08**	1.32	0.73	0.47	0.77	0.65	0.54	0.33	−0.29	−0.44	−0.41	−0.30	−0.74
-6	0.14	0.43	0.41	0.37	−0.21	0.07	0.15	−0.22	−0.22	0.02	0.11	0.18	0.00	0.00	−0.28
-5	0.62	1.54	2.43***	1.57	0.80	0.05	0.07	0.16	0.10	0.34	−0.46	−0.80	−0.55	−0.50	−0.49
-4	−0.27	−1.00	−1.03	−1.04	−0.81	0.04	0.07	0.20	0.15	0.42	−0.29	−0.35	−1.02	−0.59	−0.57
-3	0.56	1.52	2.32**	2.00**	1.15	−0.37	−0.80	−1.18	−0.86	−0.52	−0.64	−0.91	−1.14	−0.71	−1.25
-2	0.10	0.36	−0.12	−0.12	−0.37	0.23	0.71	0.30	0.41	0.46	−1.44	−1.52	−2.67***	−1.33	−0.91
-1	0.49	1.78*	1.94*	1.92*	1.36	0.20	0.43	0.46	0.42	−0.52	0.09	0.11	0.88	0.55	−0.17
0	0.97	0.75	1.59	0.32	−0.24	−0.64	−0.59	−3.06***	−1.23	−0.82	−11.55	−3.38***	−26.91***	−3.30***	−2.37**
1	−2.54	−3.46***	−10.23***	−3.71***	−2.48***	−3.56	−3.85***	−9.26***	−4.72***	−2.89***	−2.49	−1.14	−3.03***	−0.61	−0.83

Panel B: Cumulative Abnormal Returns

Event window	**Investment N=131**					**General N=74**					**Recapitalisation N=71**				
	$\overline{CAR}$ (%)	**t-test**	**Patell Z**	**BMP**	**Wilcox.**	$\overline{CAR}$ (%)	**t-test**	**Patell Z**	**BMP**	**Wilcox.**	$\overline{CAR}$ (%)	**t-test**	**Patell Z**	**BMP**	**Wilcox.**
[-25,-25]	−0.28	−0.88	0.03	0.08	−0.40	1.55	1.58	2.26**	1.12	0.43	−1.43	−2.93***	−2.63***	−2.24**	−1.14
[-25,-24]	−0.01	0.02	0.23	0.28	−0.37	1.38	1.62	1.27	1.03	−0.03	−0.32	−0.61	−0.38	−0.35	0.02
[-25,-23]	0.35	0.79	0.63	0.67	−0.03	2.10	1.70*	1.55	1.26	0.32	−0.43	−0.57	−0.52	−0.49	−0.29
[-25,-22]	0.71	1.39	1.32	1.32	0.25	2.91	2.28**	2.31**	2.13**	1.05	−1.45	−1.81*	−1.56	−1.39	−1.16
[-25,-21]	0.38	0.64	0.69	0.66	0.03	3.30	2.24**	2.20**	2.00**	1.04	−1.86	−2.11**	−1.86*	−1.69*	−1.21
[-25,-20]	0.59	0.90	0.98	0.95	0.49	3.90	2.59***	2.95***	2.63***	1.35	−2.12	−2.25**	−1.90*	−1.70*	−1.35
[-25,-19]	0.80	1.21	1.14	1.19	0.79	4.18	2.53***	2.71***	2.35**	1.21	−1.44	−1.53	−1.23	−1.31	−0.73
[-25,-18]	0.85	1.05	1.23	1.14	0.67	4.26	2.64***	2.35**	2.07**	1.42	−2.11	−2.07**	−1.48	−1.54	−0.91
[-25,-17]	0.65	0.79	0.99	0.91	0.48	4.54	2.81***	2.52***	2.21**	1.52	−3.01	−2.67***	−2.19**	−2.33**	−1.08
[-25,-16]	0.32	0.37	0.70	0.65	0.36	4.68	2.83***	2.25**	1.96*	1.58	−3.29	−2.75***	−2.11**	−2.39***	−1.04
[-25,-15]	0.33	0.35	0.69	0.63	0.31	5.59	2.88***	2.51***	2.10**	1.64	−3.22	−2.22**	−2.07**	−2.20**	−0.97
[-25,-14]	0.11	0.12	0.43	0.39	0.16	5.08	2.54***	2.02**	1.76*	1.12	−2.72	−1.79*	−1.82*	−2.09**	−0.91
[-25,-13]	0.30	0.28	0.51	0.45	0.26	5.66	2.72***	2.24**	1.99*	1.50	−3.04	−2.04**	−1.85*	−1.85*	−1.04
[-25,-12]	0.24	0.20	0.70	0.59	0.38	5.11	2.40***	1.93*	1.80*	1.14	−4.21	−2.32**	−2.21**	−2.21**	−1.37
[-25,-11]	1.26	0.92	1.50	1.27	0.88	4.55	2.08**	1.52	1.39	0.83	−4.54	−2.17**	−2.51***	−2.26**	−1.29
[-25,-10]	1.00	0.64	0.98	0.77	0.35	4.72	2.14**	1.61	1.54	0.84	−4.94	−1.91*	−2.80***	−2.35**	−1.22
[-25,-9]	1.52	0.98	1.57	1.29	0.73	4.81	2.10**	1.49	1.37	0.86	−5.29	−2.08**	−2.89***	−2.46***	−1.38
[-25,-8]	2.04	1.29	1.75*	1.38	0.63	5.84	2.56***	1.93*	1.87*	1.20	−6.17	−2.53***	−3.27***	−2.46***	−1.41
[-25,-7]	2.37	1.45	2.18**	1.71*	0.82	6.31	2.51***	2.03**	1.83*	1.29	−6.46	−2.53***	−3.28***	−2.35**	−1.23
[-25,-6]	2.51	1.53	2.21**	1.78*	1.07	6.38	2.41***	1.93*	1.69*	1.25	−6.35	−2.49***	−3.20***	−2.20**	−1.21
[-25,-5]	3.13	1.85*	2.69***	2.19**	1.23	6.43	2.25**	1.92*	1.55	1.35	−6.81	−2.60***	−3.24***	−2.41***	−1.35
[-25,-4]	2.85	1.65	2.41***	1.96*	1.10	6.47	2.05**	1.92*	1.54	1.37	−7.11	−2.60***	−3.39***	−2.26**	−1.55
[-25,-3]	3.41	1.86*	2.84**	2.23**	1.18	6.11	1.91*	1.63	1.28	1.37	−7.74	−2.77***	−3.55***	−2.35**	−1.66
[-25,-2]	3.51	1.96*	2.76***	2.22**	1.21	6.34	1.96*	1.66	1.33	1.30	−9.19	−3.04***	−4.02***	−2.69***	−1.66
[-25,-1]	4.00	2.14**	3.09***	2.43***	1.24	6.53	1.96*	1.71*	1.35	1.29	−9.10	−2.95***	−3.76***	−2.60***	−1.52
[-25,0]	4.98	2.08**	3.34***	2.03**	1.33	5.89	1.68*	1.08	0.79	0.83	−20.64	−4.16***	−8.97***	−3.76***	−2.64***
[-25,1]	2.44	1.05	1.31	0.82	0.40	2.33	0.67	−0.72	−0.54	−0.10	−23.14	−4.66***	−9.38***	−4.11***	−2.76***

Note: The table presents the abnormal- and cumulative average abnormal returns for the 3 categories Investments, General & Recapitalisation in the event window [-25,1]. Panel A describes the average abnormal returns with corresponding test-statistics, while Panel B describes the cumulative average abnormal returns. We include a t-test, Patell Z test, BMP test and Wilcoxon rank test for both the abnormal- and cumulative average abnormal returns to investigate whether the different returns are equal to zero. *, ** and *** denote test-statistics significant at 10 %, 5 % and 1 %, respectively. Please see Appendix A for calculation of the different test-statistics.

From Panel B in Table 3, we observe that the pre-announcement buildup in $\overline{CAR}$ for the *Investment*- and *General* samples, are significantly different from zero. Following the discussion from the first part of the analysis, we conclude that the significant buildup in $\overline{CAR}$ are likely to be caused by other factors than illegal insider trading. Consequently, we will not look further into these offerings.

However, we will investigate the *Recapitalisation* offerings further, as our results indicate a potential for illegal insider trading in this category. Similar to the *M&A* sample, we observe a substantial negative average abnormal return of -11.55 % for the *Recapitalisation* sample at announcement date. Similar to the *M&A* sample, this suggests that the announcement generally came as a surprise to the market. Nevertheless, approximately half (-9.10 %) of the total decrease (-20.64 %) in $\overline{CAR}$ occurs prior to the announcement. The development in $\overline{CAR}$ is even greater than what we observe from the *M&A* sample in absolute terms. Furthermore, we observe that the $\overline{CAR}$s are consistently negative in the 18 days prior to the announcement. The different statistical tests on $\overline{CAR}$ suggests that the development is no coincidence, as the t-test, patell Z test and the BMP test imply that $\overline{CAR}$ is different from zero 17 days prior to announcement. These findings might suggest that there is a degree of illegal insider trading prior to recapitalisation motivated SEOs. There might, however, be other factors that explain the negative development in $\overline{CAR}$ for the *Recapitalisation* sample, which we investigate further in the subsequent sections.

For robustness of the results in this section, we also calculate the abnormal returns based on the Fama-French 3-factor model (see Appendix A5). Consistent with Kothari and Warner (2006), this does not substantially influence our results. They argue that short-term event studies are largely immune to misspecification in estimating abnormal returns.

5.2 Abnormal Trading Volume

As we observe in the previous section, the buildup in $\overline{CAR}$ prior to the announcement for the M&A are relatively small compared to previous research. Gao and Oler (2004) argues that significant buy (sell) side transactions of illegal insiders could be offset by significant sell (buy) side transactions from uninformed investors, as these investors interpret increase (decrease) in share price as over (under) valuation of the stock. This will result in a relatively steady share price. However, if the aforementioned occurrence is true then we should also experience significant abnormal trading volume prior to the significant abnormal returns. From Table 4 we do not observe such a lag in significant abnormal returns that could substantiate the statements from Gao and Oler (2004) for the M&As.

Table 4: Abnormal- return and volume, M&A

Day	**N**	**M&A - Abnormal Returns & Abnormal Volumes**					
		$\overline{AR}$	$\overline{AR}$ t-Score	$\overline{CAR}$	$\overline{CAR}$ t-Score	$\overline{AV}$	$\overline{AV}$ t-Score
-13	129	0.05	0.13	0.05	0.13	0.11	0.99
-12	129	0.72	1.84*	0.76	1.45	0.23	1.89*
-11	129	0.47	1.35	1.23	2.19**	0.25	2.16**
-10	129	0.40	1.22	1.63	2.65***	0.18	1.68*
-9	129	−0.18	−0.62	1.45	2.18**	0.08	0.65
-8	129	0.08	0.28	1.53	1.91*	0.20	1.68*
-7	129	0.64	1.83*	2.17	2.39***	0.13	1.04
-6	129	−0.24	−0.78	1.93	2.02**	0.07	0.61
-5	129	0.00	0.00	1.93	2.06**	0.19	1.63
-4	129	0.59	1.97*	2.52	2.55***	0.13	1.10
-3	129	0.82	2.40***	3.34	3.24***	0.34	3.04***
-2	129	0.46	1.60	3.80	3.52***	0.26	2.05**
-1	129	0.94	3.03***	4.74	4.10***	0.39	3.34***
0	129	15.10	7.60***	19.84	11.52***	3.01	16.69***

Note: This table provides the average abnormal returns, cumulative average abnormal returns and average abnormal volume with corresponding t-test statistics for the M&A sample. Average abnormal volume is the difference between daily trading volume and the average trading volume of the same firm over the estimation period [-126,-26]. These abnormal volumes are averaged across firms. *, **, and *** denote test-statistics significant at 10 %, 5 % and 1 % respectively.

When we look at the *Recapitalisation* category in Table 5 we observe that there are several days of significant abnormal trading volume prior to significant abnormal returns. Gao and Oler (2004) argues that this lag between abnormal returns and abnormal volume can be interpreted as the effect of illegal insider trading.

Table 5: Abnormal- return and volume, Recapitalisation

Day	N	Recapitalisation - Abnormal Returns & Abnormal volumes					
		$\overline{AR}$	$\overline{AR}$ t-Score	$\overline{CAR}$	$\overline{CAR}$ t-Score	$\overline{AV}$	$\overline{AV}$ t-Score
-25	71	−1.43	−1.62	−1.43	−2.93***	0.04	0.25
-24	71	1.10	1.50	−0.32	−0.61	0.32	2.32**
-23	71	−0.11	−0.23	−0.43	−0.57	0.35	2.50***
-22	71	−1.02	−1.54	−1.45	−1.81*	0.17	1.16
-21	71	−0.41	−0.77	−1.86	−2.11**	0.39	2.64***
-20	71	−0.25	−0.33	−2.12	−2.25**	0.14	0.91
-19	71	0.67	0.92	−1.44	−1.53	0.25	1.68*
-18	71	−0.67	−0.66	−2.11	−2.07**	0.15	0.99
-17	71	−0.90	−1.05	−3.01	−2.67***	−0.04	-0.26
-16	71	−0.28	−0.45	−3.29	−2.75***	0.12	0.84
-15	71	0.07	0.12	−3.22	−2.22**	0.27	2.06**
-14	71	0.50	0.48	−2.72	−1.78*	0.17	1.22
-13	71	−0.32	−0.32	−3.04	−1.88*	0.44	2.37***
-12	71	−1.16	−1.48	−4.21	−2.22**	0.16	0.94
-11	71	−0.33	−0.37	−4.54	−2.07**	0.15	0.88
-10	71	−0.40	−0.66	−4.94	−1.85*	0.21	1.42
-9	71	−0.35	−0.70	−5.29	−1.99**	0.15	1.00
-8	71	−0.88	−1.21	−6.17	−2.42***	0.22	1.38
-7	71	−0.29	−0.44	−6.46	−2.46***	0.27	1.58
-6	71	0.11	0.18	−6.35	−2.42***	0.27	1.73*
-5	71	−0.46	−0.80	−6.81	−2.54***	0.35	2.201**
-4	71	−0.29	−0.35	−7.11	−2.54***	0.17	1.11
-3	71	−0.64	−0.91	−7.74	−2.73***	0.43	3.28***
-2	71	−1.44	−1.52	−9.19	−3.03***	0.45	2.95***
-1	71	0.09	0.11	−9.10	−2.96***	0.40	2.60***
0	71	−11.55	−3.38***	−20.64	−4.29***	1.14	5.34***

Note: This table provides the average abnormal returns, cumulative average abnormal returns and average abnormal volume with corresponding t-test statistics for the Recapitalisation sample. Average abnormal volume is the difference between daily trading volume and the average trading volume of the same firm over the estimation period [-126,-26]. These abnormal volumes are averaged across firms. *, ** and *** denote test-statistics significant at 10 %, 5 %, and 1 %, respectively.

As mentioned, Gao and Oler (2004) argues that the existence of abnormal volume prior to an announcement can indicate a degree of illegal insider trading. This is further supported by Keown and Pinkerton (1981) who suggest that surges in volumes prior to an announcement might indicate illegal insider trading. However Jarrell and Poulsen (1989) claims that abnormal volume indicates a level of rumors. Since the literature is somewhat inconsistent as to how to interpret this measure, we introduce Google search volume as a new measure of investor attention. Rumors about an upcoming event will undoubtedly attract search attention on Google. Moreover, a single investor with private information can account for significant amount of a potential abnormal trading volume, whereas a single person will not have the same effect on Google search volume. Consequently, we believe this measure will isolate the rumor effect in a more accurate way.

5.3 Abnormal Google Search

Following Jarrell and Poulsen (1989), we argue that a buildup in $\overline{CAR}$ prior to an announcement cannot in itself provide evidence of illegal insider trading. There can be many justifications for such a buildup that needs be accounted for. The existence of rumors and market anticipation before an upcoming event is one factor that can contribute to a pre-announcement buildup in CAR. Existing literature have mainly used media speculation as a measure of these factors (see Jarrell Paulson, 1989; Sanders Zdanowics, 1993). In this paper, however, we use Google search frequency as a direct measure of investor attention, to distinguish illegal insider trading from rumors and market anticipation. Da et al. (2013) argues that a search on a stock on Google is a revealed attention measure. If rumors about an upcoming merger or seasoned equity offering circulate, then it will undoubtedly attract investor attention. Hence, we can use this information to isolate events where there has been an abnormal number of search, indicating the existence of rumors and/or market anticipation.

We obtain Google search volume data on a total of 90 *M&A*s and 63 *Recapitalisations*. These are divided into two subsets by the median abnormal search volume. Furthermore, $\overline{CAR}$ is calculated for each of the four sub-samples. The results are presented in Table 6.

Table 6: $\overline{CAR}$ split by Search volume

Day	Full Google Trends Sample					
	M&A			Recapitalisation		
	High ASVI $\overline{CAR}$ (%)	Low ASVI $\overline{CAR}$ (%)	two sample t-statistic	High ASVI $\overline{CAR}$ (%)	Low ASVI $\overline{CAR}$ (%)	two sample t-statistic
-25				−2.50	−0.84	−2.06**
-24				−0.49	−1.00	0.64
-23				−0.63	−0.76	0.28
-22				−2.04	−1.96	0.09
-21				−2.28	−2.29	0.11
-20				−0.99	−3.06	1.18
-19				−0.68	−1.70	0.62
-18				−2.22	−1.85	−0.09
-17				−4.07	−2.15	−0.87
-16				−4.99	−2.40	−1.21
-15				−4.83	−2.53	−0.91
-14				−3.28	−2.81	−0.12
-13	−0.18	0.08	−0.39	−3.98	−2.29	−0.44
-12	0.09	0.03	0.07	−4.65	−2.93	−0.46
-11	0.41	0.16	0.24	−5.62	−3.33	−0.62
-10	0.79	0.18	0.50	−5.84	−3.55	−0.61
-9	0.43	−0.13	0.44	−5.99	−3.84	−0.55
-8	0.56	−0.45	0.71	−6.20	−4.65	−0.37
-7	1.77	0.02	1.01	−6.95	−4.91	−0.48
-6	2.12	−1.00	1.65	−5.72	−5.54	0.01
-5	2.07	−0.66	1.51	−6.36	−5.76	−0.10
-4	2.55	−0.53	1.73*	−5.57	−6.31	0.23
-3	3.51	−0.23	1.96*	−5.80	−7.75	0.51
-2	3.93	0.05	2.02**	−6.19	−10.15	0.93
-1	4.27	0.92	1.58	−6.16	−9.46	0.78
0	20.90	17.72	0.71	−15.37	−25.97	1.36

Note: In this table, we investigate the full Google Trends sample consisting of 90 *M&A* observations and 63 *Recapitalisations*. We divide each sample into two sub-samples consisting of the firms with the highest- and lowest ASVI, split by the median observation. We compare the $\overline{CAR}$ development between the sub-samples. For comparison, we add a two sample t-test to test if the two sub-samples in each category are equal to each other. The M&A-sample starts at 13 trading days prior to the announcement as the interesting development in $\overline{CAR}$ starts at this point. Similarly, we include 25 trading days prior to the announcement for the *Recapitalisation* sample.

As we observe, the buildup in $\overline{CAR}$ is almost entirely driven by companies with a high abnormal search volume prior to the public announcement of the M&A. This result indicates that the buildup in $\overline{CAR}$ for *M&A*s is a result of market anticipation or rumors of a possible M&A. A two-sample t-test also displays that the $\overline{CAR}$, for the different samples are significantly different from each other. In addition, a one sample t-test on the low ASVI sample shows that the $\overline{CAR}$s are not significantly different from zero. These findings are interesting because they suggest that there is not systematic illegal insider trading prior to M&A announcements on OSE, in contrast to several previous studies on other markets (see Keown and Pinkerton, 1981; Jain and Sunderman, 2014).

When we look at the buildup in $\overline{CAR}$ for the *Recapitalisation* sub-samples we observe the opposite effect. The buildup in $\overline{CAR}$ is larger for the firms with a low search volume prior to the announcement. The t-statistic shows, however, that the $\overline{CAR}$s are not significantly different from each other. This result indicates that the buildup in $\overline{CAR}$ may not be driven by rumors, but in fact illegal insider trading.

However, Barber and Odean (2008) and Da et al. (2011) find that stocks with an increase in ASVI are associated with an outperformance in stock returns. Barber and Odean (2008) uses the argument that individual investors are net buyers of attention-grabbing securities. The reasoning behind this is that when investors are buying stock they can choose from a pool of alternatives. However, when they are selling, they tend to sell only stocks they already own. Following this argumentation, we would expect a smaller effect of our attention measure on *Recapitalisation* than on *M&A*.

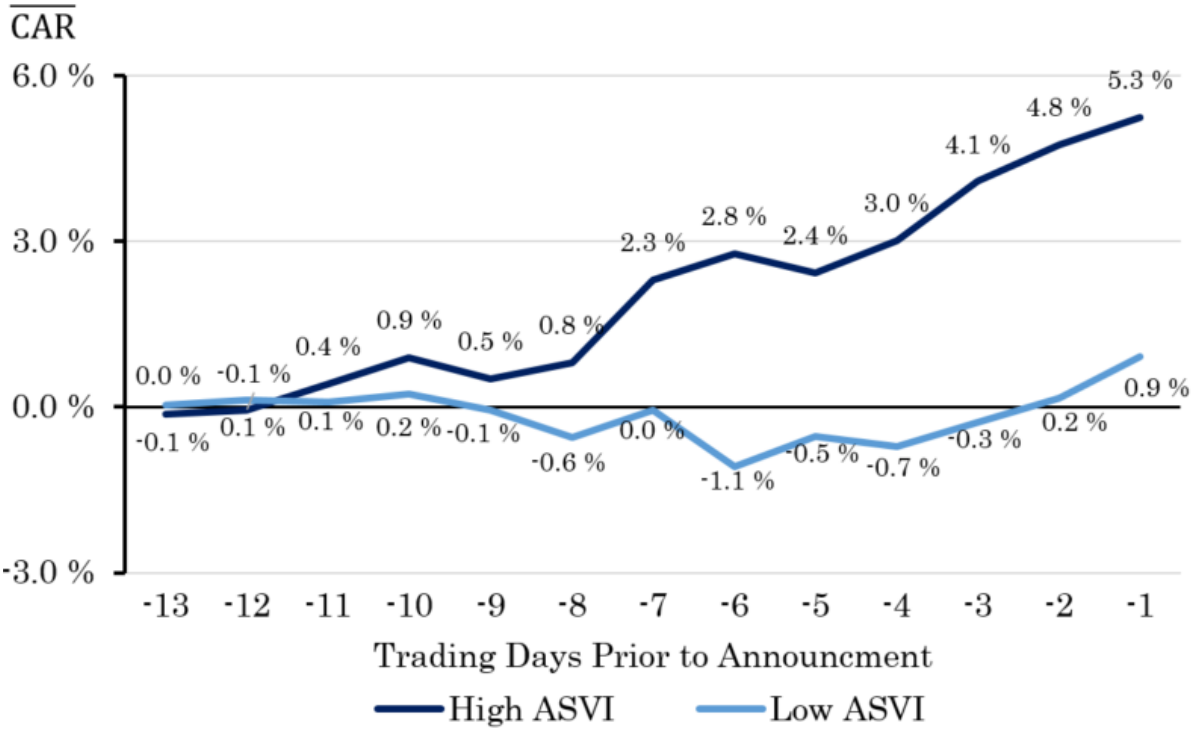
Like Da et al. (2011), we find some of the searches as *noisy*. This occurs when the abnormal search volume (ASVI) can be explained by other factors than investor attention. Some examples of such *noisy* observations are searches on Norwegian Air Shuttle, XXL and Komplett, where the purpose of the search is likely to be related to other factors than the stock. For example a search on Norwegian Air Shuttle is likely to be related to customers wanting to buy flight tickets, and the search volume will be correlated with travelling seasons rather than investor attention. These observations bring noise to the data and may cause biased results. We manually go through all the companies in the sample and flag these observations. For robustness, we repeat the abovementioned exercise with data were *noisy* observations are excluded. After removing the *noisy* observations, we are left with 78 and 59 observations for the *M&A* and *Recapitalisation* sample, respectively. A list of the *noisy* company observations is found in Appendix A4. The results from the filtered samples are presented in Table 7 below.

Table 7: $\overline{CAR}$ split by Search volume, ex. *noisy* observations

Day	Google Trends Sample after removing *noisy* observations — M&A			Recapitalisation		
	High ASVI $\overline{CAR}$ (%)	Low ASVI $\overline{CAR}$ (%)	two sample t-statistic	High ASVI $\overline{CAR}$ (%)	Low ASVI $\overline{CAR}$ (%)	two sample t-statistic
-25				−2.34	−0.88	−0.73
-24				0.07	−0.97	0.42
-23				0.09	−0.69	0.31
-22				−0.74	−1.90	0.48
-21				−1.23	−2.21	0.35
-20				0.18	−3.08	1.06
-19				0.63	−1.51	0.78
-18				−1.05	−1.61	0.18
-17				−3.31	−1.81	−0.44
-16				−5.11	−2.15	−0.81
-15				−4.81	−2.30	−0.62
-14				−3.20	−2.49	−0.19
-13	−0.13	0.04	−0.24	−4.09	−1.86	−0.49
-12	−0.05	0.14	−0.19	−4.92	−2.54	−0.51
-11	0.42	0.09	0.28	−6.09	−2.94	−0.57
-10	0.90	0.23	0.48	−6.27	−3.23	−0.52
-9	0.51	−0.06	0.40	−6.44	−3.54	−0.47
-8	0.81	−0.56	0.85	−6.77	−4.29	−0.36
-7	2.31	−0.05	1.21	−7.75	−4.68	−0.41
-6	2.78	−1.08	1.81*	−6.84	−5.50	−0.17
-5	2.44	−0.53	1.45	−8.23	−5.78	−0.34
-4	3.02	−0.71	1.84*	−9.03	−6.34	−0.36
-3	4.09	−0.27	2.04**	−9.06	−7.07	−0.26
-2	4.76	0.17	2.15**	−8.84	−9.69	0.11
-1	5.26	0.91	1.87*	−8.63	−8.92	0.04
0	19.78	20.11	−0.07	−15.85	−25.14	0.82

Note: The table presents the development in cumulative abnormal returns for the Google Trends sample after removing *noisy* observations for both *M&A*s and *Recapitalisations*. There are 78 *M&A*s and 59 *Recapitalisations* left in the samples when *noisy* observations are excluded. We divide each sample into two sub-samples consisting of the firms with the highest- and lowest ASVI, split on the median observation. We compare the $\overline{CAR}$ development between the sub-samples. For comparison, we add a two sample t-test to test if the two sub-samples in each category are equal to each other. The M&A-sample starts at 13 trading days prior to the announcement as the interesting development in $\overline{CAR}$ starts at this point. Similarly, we include 25 trading days prior to the announcement for the *Recapitalisation* sample.

Figure 5: $\overline{CAR}$-development for sub-samples excluded *noisy* observation



Note: The chart shows the development in $\overline{CAR}$ for the two sub-samples with High- and Low ASVI in the M&A sample. Furthermore, noisy observations are removed. On the x-axis, we include the trading days prior to the announcement date in the interval [-13,-1].

As we see from the Table 7 and Figure 5, the difference in $\overline{CAR}$ between the high- and low ASVI samples become even clearer for the *M&A*s when we remove *noisy* observations. This further substantiates our previous findings on the *M&A* sample and indicates that the abnormal returns may not be driven by illegal insider trading. For the *Recapitalisation* category, the results remain similar to the ones found when investigating the whole Google Search sample, thus indicating that the pre-announcement $\overline{CAR}$ is driven by other factors than rumors. One of these factors could be illegal insider trading.

To summarize our findings from the first parts of the analysis, we have presented results indicating that there is a low degree of illegal insider trading for the offerings categorized as *Investments* and *General*. The conclusion is drawn from the fact that the $\overline{CAR}$ is surging prior to the announcement for both samples, while the opposite development is seen in the $\overline{CAR}$. after the announcement day. There still might exist some degree of illegal insider trading, however the possible criminal offence is not decisive for the direction of the share price development.

Furthermore, we have looked at different rumor indicators such as abnormal trading volume and abnormal search volume, collected from Google Trends. The latter indicator suggests that the build-up in $\overline{CAR}$ before *M&A* announcements stem from rumors. Following the net buying hypothesis presented by Barber and Odean (2007), further discussed by Da et al. (2011), it is reasonable that we do not observe the same difference in $\overline{CAR}$ between high- and low ASVI in the *Recapitalisation* sample. We therefore conclude differently in the two subsets in this section. Consequently, we provide two different angles on the cross-sectional analysis for the two subsets *M&A* and *Recapitalisation* in the following section.

5.4 Cross-Sectional Analysis

In this section, we present results from cross-sectional regression analysis on CAR in the *M&A*- and *Recapitalisation* samples. We want to check whether other variables than illegal insider trading can explain the variation in CAR between the different events. Also, we are interested in looking at how much of the variation in CAR a Google Trend binary variable can explain and how this variable is affected when including multiple other independent variables. *Noisy* observations are excluded in this variable. We will focus most on the latter in the *M&A* regressions given the results from the previous section. It should be mentioned that these types of cross-sectional regressions usually have a low explanatory power, at below 10 % (Eckbo et al., 2007).

We split the regressions into two different tables, where Table 8 and Table 9 present regressions for the *M&A* and *Recapitalisation* samples respectively. The dependent variable is the cumulative abnormal return for the different firms in the event period (-13,-1) for the *M&A* sample and (-25,-1) for the *Recapitalisation* sample. We include different firm- and deal specific variables, and present coefficient estimates from equation 12 in addition to the corresponding standard errors. The standard errors are adjusted for heteroscedasticity and clustering. Following MacKinlay (1997) and Silva and Bilinski (2015), we adjust for clustering across the firm dimension as the residuals might be correlated. A problem of multicollinearity can arise if there is high correlation between the explanatory variables (Woolridge, 2016). As the correlation between the different explanatory variables is low (see Appendix A3), we do not deem this a substantial problem for our cross-sectional analysis. In all *M&A* regression models we add indicator variables for year and industry, to account for yearly- and industry fixed effects (FE), while these are included in 4 out of 5 regressions on the *Recapitalistion* sample.

5.4.1 M&A Regression Analysis

We will now address the explanatory variables that are included in the different M&A regression models. The aim of the regressions performed on the *M&A* sample is to; 1) investigate whether the binary variable *High ASVI* is significantly different from zero when including more explanatory variables and 2) to look at other variables that might explain some of the pre-announcement build-up in $\overline{CAR}$. In Model (1), we only include the binary indicator for abnormal search volume, where *Low ASVI* is the omitted variable. In model (2) we include deal specific characteristics as explanatory variables, such as number of bidders on the target firm, domestic versus international acquirer and relative target deal size. The two former variables are binary, that take the value 1 if there are more than one bidder on the target firm, and if the acquirer is foreign respectively. The relative target deal size is a continuous variable that can take values in the interval [0.05,1] (see section 3.1). We add the natural logarithm of market capitalization and book-to-market ratio in Model (3) to also control for valuation factors of the target firm. Lastly, we include target financial characteristics that control for leverage and profitability of the firm. We provide explanation for the selection of our explanatory variables in the Section 4.4.1.

Table 8: Cross-Sectional Regression for *M&A*

Dependent variable: CAR(-13,-1)	**Model 1**	**Model 2**	**Model 3**	**Model 4**
High abnormal search	0.119***	0.114***	0.123***	0.115**
	(0.04)	(0.04)	(0.04)	(0.04)
Multiple bidders		-0.037	-0.013	-0.004
		(0.06)	(0.06)	(0.06)
For. Acquirer		-0.054	-0.046	-0.059
		(0.05)	(0.05)	(0.05)
Rel. Deal-Size		0.056	0.018	0.021
		(0.06)	(0.07)	(0.07)
ln(Market Cap)			-0.010	-0.009
			(0.02)	(0.02)
ln(B2M)			-0.062**	-0.061*
			(0.03)	(0.03)
ln(Turnover)				0.019
				(0.02)
Leverage				0.008
				(0.12)
ROA				-0.113
				(0.20)
Constant	-0.055	-0.028	0.192	0.208
	(0.10)	(0.11)	(0.30)	(0.29)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R^2	0.465	0.482	0.529	0.550
adj. R^2	0.247	0.228	0.258	0.243
N	77	77	75	75

Note: This table presents the results from the cross-sectional analysis done on the M&A sample. The dependent variable is the cumulative average abnormal returns measured over a 13 day period prior to the annoouncement of the M&As. We elaborate on the reason for inclusion of the explanatory variables in Section 4.4.1. We report explanatory variable coefficient and corresponding standard errors adjusted for heteroscedastisity and clustering. All 4 models include yearly- and industry fixed effects. Moreover, *, ** and *** denote test-statistics significant at 10 %, 5 % and 1 %, respectively.

The main insight we obtain from Model (1) is that the CAR of the firms with high abnormal search volume, is significantly different from zero when accounting for fixed effects. This finding supports the conclusion drawn in the previous section, where we found, without considering fixed effects, that there was a significant difference in CAR between high- and low ASVI observations. The adjusted R-squared is 0.247 in Model (1), implying that the model explains some of the variation in CAR.

From Model (2) we still observe that the indicator variable *high* $ASVI$ is statistically significant at a 1 % significance level. All the deal specific variables are insignificant, and they seem to add noise to the regression model as the adjusted R-squared decreases.

The key takeaways from Model (3) is that by adding both the target market capitalization and book-to-market ratio, the model performs better at explaining the variation in CAR. This is mainly due to the book-to-market variable, which is significant at a 5 % level. The coefficient is negative, implying that target firms with low book-to-market ratios (growth firms) have higher abnormal returns than high book-to-market target firms (value firms) in the event period. This is inconsistent with findings of Jain and Sunderman (2014) who found the opposite effect.

In model (4) we add the financial characteristics of the target firm to control for pre-announcement profitability and leverage. The high ASVI binary variable remains significant, however no longer at a 1 % significance level. Also, the significance of the book-to-market ratio falls. The added variables seem to add noise to Model (3) as we observe that the explanatory power of the model decreases.

The most noteworthy findings from the cross-sectional regression on the M&A sample is that the *High* $ASVI$ variable remains significant, although we include other variables in the regression. This is consistent with our findings in Section 5.3. Based on the results from the regression models, we find no evidence of illegal insider trading regarding the M&A sample.

5.4.2 Recapitalisation Regression Analysis

In the *Recapitalisation* cross-sectional regression, our main objective is to explore whether there are any other variables that explain the negative development in $\overline{CAR}$ for the *Recapitalisations* in the event window (-25,-1). In model (1) we only include the high abnormal search indicator for robustness to the results found in Section 5.1. We exclude FE in this model for the interpretation of the constant term. In model (2) we add a binary variable for flotation-method and a continuous variable for relative deal size. The binary variable *Accelerated* take the value 1 if the flotation-method is executed as a private placement. In model (3) we add the natural logarithm to the valuation metrics market capitalization and book-to-market. The next model include all variables including stock turnover, financial characteristics, and yearly- and industry fixed effects. In model (5) we zoom in on the financial characteristics.

Table 9: Cross-Sectional Regression for *Recapitalisation*

Dependent variable: CAR(-25,-1)	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
High abnormal search	0.005	0.049	0.059	0.037	0.070
	(0.08)	(0.09)	(0.08)	(0.07)	(0.07)
Accelerated		-0.081	-0.074	-0.023	
		(0.13)	(0.08)	(0.07)	
Rel. Deal-Size		-0.003	0.007	0.008	
		(0.02)	(0.01)	(0.01)	
ln(Market Cap)			-0.002	-0.003	
			(0.02)	(0.03)	
ln(B2M)			-0.016	-0.024	
			(0.03)	(0.03)	
ln(Turnover)				-0.020	
				(0.03)	
Leverage				-0.391*	-0.505**
				(0.21)	(0.20)
ROA				0.140**	0.108**
				(0.06)	(0.05)
Constant	-0.091*	0.365	0.212	0.290	0.205*
	(0.05)	(0.32)	(0.24)	(0.37)	(0.12)
Year FE	No	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	Yes	Yes
R^2	0.000	0.336	0.459	0.708	0.589
adj. R^2	-0.017	-0.081	-0.061	0.214	0.241
N	59	58	50	44	49

Note: This table presents the results from the cross-sectional analysis done on the *Recapitalisation*-sample . The dependent variable is the cumulative average abnormal returns measured over a 15 day period prior to the announcement of the *Recapitalisation*s. We elaborate on the reason for inclusion of the explanatory variables in Section 4.4.1. We report explanatory variable coefficient and corresponding standard errors adjusted for heteroscedastisity and clustering. 4 of 5 models include yearly- and industry fixed effects. Moreover, *, ** and *** denote test-statistics significant at 10 %, 5 % and 1 %, respectively.

In Model (1), we observe results consistent to what we found in the previous section: The binary ASVI-variable explains close to nothing of the increase in CAR as the R-squared equals 0.000. We have not included fixed effects at this point on purpose for interpretation of the constant coefficient. The constant expresses that when looking at the observations with low ASVI, the CAR is equal to -9.1 % on average, consistent with the results from

Table 7. The constant is also significant at a 10 % level.

When we add the binary variable *Accelerated* and *Relative deal size* in model (2), all explanatory variables are insignificant and the model explains close to nothing of the variation in CAR. In model (3) we add both market capitalization and book-to-market ratio of the issuer. The inclusion of these variables does not improve the explanatory power of the model.

In model (4) we add all the our explanatory variable, including yearly- and industry fixed effects. The adjusted R-squared has increased to 21.4 %, implying a stronger model than model (3). The financial characteristics *Leverage* and *ROA* are significant. Consequently, we want to look closer at these variable as they seem to be the most important factors in explaining the pre-announcement buildup in $\overline{CAR}$.

When only adding the $ASVI$ term, *ROA* and *Leverage* in model (5), we observe that both the *ROA* and *Leverage* is significant at a 5 % level. The R-squared has increased to 24.1 %. The results from model (5) are important. These findings suggest that the financial characteristics of the firm are important factors explaining the plunge in $\overline{CAR}$ prior to the announcement. From an intuitive perspective it adds up, as one would expect sophisticated investors to monitor their calculations on the probability of an emergency offering and act accordingly. The event window we use is fairly wide (-25,-1). 25 trading days include on average 38 regular days in the *Recapitalisation* sample. From a manual search we find observations where the quarterly numbers are released in the event window, which is intuitive as quarterly results are released approximately every 90 days. It is reason to believe that the release of quarterly results in an event window prior to a *Recapitalisation* will on average have an unfavourable impact on abnormal returns, as the company might release new negative information or shed light on the financial situation of the firm. However, we cannot reject that illegal insider trading explains some of the development in $\overline{CAR}$ as the regression model only explains 24.1% of the variation in CAR and approximately half of the total buildup in $\overline{CAR}$ occurs prior to the public announcement.

6 Conclusion

In this thesis we examine the illegal insider trading activity prior to M&A- and SEO announcements on Oslo Stock Exchange. Using a sample of 405 successful M&A- and SEO transactions between 2000 and 2019, we apply the Event-study methodology, as described by MacKinlay (1997), to calculate $\overline{CAR}$ prior to the public announcements of these deals. A significant buildup in $\overline{CAR}$ prior to a public announcement indicates a degree of illegal insider trading, provided that information about the upcoming transaction is not anticipated by the market. We introduce *ex ante* stated intended use of proceeds as a differentiation variable to distinguish between different SEOs, as existing literature finds that the market reaction is dependent on the stated motivation behind the offering (see Autore et al. 2009; Silva and Belinski, 2013).

Our initial results suggests that there could be a degree of illegal insider trading prior to M&A announcements, with a significant $\overline{CAR}$ of 4,7 % during an event window stretching from 13 trading days- to 1 trading day prior to the public announcement (-13,-1). However, this result is relatively small compared to similar research on other markets (e.g Keown and Pinkerton, 1981; King, 2009). Subsequently we find that SEOs, categorized as *Recapitalisations*, experience approximately half of the total decrease in $\overline{CAR}$ prior to the public announcement. This might indicate a level of short selling by informed insiders before the information is available to the market. SEOs categorized as either *General* or *Investment* do experience a significant positive buildup in $\overline{CAR}$ prior to public announcements. However, the market reacts in the opposite direction upon disclosure of the transaction. As the $\overline{AR}$s move in the opposite direction of what we would expect with substantial illegal insider trading prior to the announcement, our main focus for the rest of the analysis is *M&A* and *Recapitalisation*.

Although some existing literature interpret significant buildup in $\overline{CAR}$ as *de facto* evidence of illegal insider trading, we add Google search volume as a proxy for investor attention. We can thus identify events where there have been abnormal search volumes, indicating information leakage. For the *M&A* category, our findings demonstrate that there is a significant difference in $\overline{CAR}$ between firms with high - and low search volume. Firms with a low degree of abnormal search experience a pre-announcement $\overline{CAR}$ close to zero.

These results suggests that the pre-announcement runup in $\overline{CAR}$ for the M&As are largely driven by rumors and/or market anticipation. However, when we apply the same methodology to the *Recapitalisation* events, we do not find a significant difference between high- and low search volume firms. As discussed in the analysis section, this can either be explained by the net buying hypothesis presented by Barber and Odean (2008) or it could in fact indicate illegal insider trading.

Moreover, we investigate whether there are other deal- or firm specific variables that may explain the pre-announcement buildups in $\overline{CAR}$ for *M&A* and *Recapitalisations* respectively. Through our cross-sectional regression analysis, we find that search volume is consistently significant in the *M&A* sample even when we control for other deal- and firm specific variables. This is consistent with our previous findings that the runup can be largely explained by market anticipation and rumors. Also consistent with our previous findings we observe that the coefficient for search volume is not significant when we run the cross-sectional regression on the *Recapitalisation*s. The most interesting results from the *Recapitalisation* regressions is that *Leverage* and *ROA* seems to explain much of the variation in CAR. This means that the financial situation of the firms can explain some of the variations in CAR. This is reasonable considering the financial distress a firm experience prior to a recapitalisation motivated offering. However, the explanatory power of the regression model is relatively low. In addition, a substantial part of the total decrease in $\overline{CAR}$ occurs prior to the public announcement. Thus we cannot exclude the possibility of systematic illegal insider trading in the *Recapitalisation* sample.

Although we do not provide clear evidence of illegal insider trading, our findings indicate that this might be the case prior to announcement of SEOs with recapitalisation motives. However, inconsistent with literature on foreign markets, our findings suggest that illegal insider trading prior to M&A announcements might not be a substantial problem on OSE.

We believe this thesis provides an important contribution to previous research as we employ Google search volume as a *direct* measure of investor attention. To the best of our knowledge this has not been done in this context before. Our results indicate that the *Recapitalisation* offerings have the most potential to attract illegal insider trading. For future research, we thus believe it is interesting to look further into these types of seasoned equity offerings.

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Appendix

A1 Statistical Tests

In order to investigate if there is any illegal insider trading prior to the different deal announcements, we apply significance testing. It is important that the test results are robust, especially as we base our second part of the analysis on the yielded results from the inferences. MacKinlay (1997) split the significance tests into two main categories: parametric- and non-parametric tests. Parametric tests are characterized as tests with specific assumptions about the distribution of abnormal returns, while in the non-parametric tests there are no such assumptions. These non-parametric tests are typically not performed in isolation but in conjunction with the parametric ones for robustness (MacKinlay, 1997).

We first test if the $\overline{AR}$s and $\overline{CAR}$s in the subgroups *M&A*, *Investment*, *General* and *Recpaitalisation* are equal to zero, following the approach of and MacKinlay (1997). To build upon the t-tests, we perform statistical inferences on $\overline{AR}$ and $\overline{CAR}$ with a standardization of the test, based on the work of Patell (1976). A further development of the test is introduced by Boehmer et al. (1991). This test (BMP) is robust to the event-induced variance. Following MacKinlay (1997), we will supplement with the non-parametric Wilcoxon Rank test.

A1.1 Cross-sectional t-test

Following MacKinlay (1997) we want to test if the $\overline{CAR}$ are significantly different from zero. To perform statistical inference on $\overline{CAR}$ under the assumption of no overlap in the event window of the different observations, we employ a two-sided cross-sectional t-test with the following statistical features (MacKinlay, 1997):

$$\overline{CAR}(\tau_1, \tau_2) \sim N[0, var(\overline{CAR}(\tau_1, \tau_2))] \tag{15}$$

The residual variance σ_ϵ^2 needed to compute the variance of the $\overline{AR}$ and thus the variance of the $\overline{CAR}$ following the relationship between $var(\overline{AR})$ and $var(\overline{CAR})$ in equation 16 and equation 17, is unknown.

$$var(\overline{CAR}(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} var(\overline{AR}_\tau) \tag{16}$$

$$var(\overline{AR}(\tau_1, \tau_2) = \frac{1}{N^2} \sum_{i=1}^{N} \sigma_\epsilon^2 \tag{17}$$

Patell (1976) states that the residual variance σ_ϵ^2 from the market model regression, where we found the α and β, is unbiased. MacKinlay (1997) further propose these residual variances as an appropriate estimator for the residual variance in equation 17. We use this estimator to compute the variance of $\overline{(AR)}$ and $\overline{(CAR)}$ from equation 16 and equation equation 17, respectively. H_0 can now be tested using:

$$\theta_1 = \frac{\overline{CAR}(\tau_1, \tau_2)}{var(\overline{CAR}(\tau_1, \tau_2))^{1/2}} \sim N(0, 1) \tag{18}$$

We similarly find t-statistics for $\overline{AR}$ using the formula:

$$\theta_1 = \frac{\overline{AR}(\tau_1, \tau_2)}{var(\overline{AR}(\tau_1, \tau_2))^{1/2}} \sim N(0, 1) \tag{19}$$

The distributional results are asymptotic with respect to both the number of securities N and the length of our estimation window (MacKinlay, 1997). This is generally not a problem for event studies as the convergence to asymptotic distributions is rather quick for the test statistics (MacKinlay, 1997). In our study, we use a large N and our estimation window is 101 trading days.

A1.2 Patell test

MacKinlay (1997) also refers to the Patell test as a common modification to the test mentioned above. The approach of Patell (1976) standardize each AR_i by dividing the AR_i with the forecast-error corrected standard deviation. Such standardization can lead to more powerful tests (MacKinlay, 1997).

$$SAR_{i,t} = \frac{AR_{i,t}}{S_{AR_{i,t}}} \tag{20}$$

Where the $SAR_{i,t}$ is the standardized abnormal return and $S_{AR_{i,t}}$ is the standard deviation of the abnormal returns in the estimation window from the test of MacKinlay (1997).

Patell (1976) adjust the standard error by the forecast error, as the event-window ARs are out-of-sample predictions. The formula for the forecast-error corrected standard deviation is derived square routing the left side of equation 21.

$$S^2_{AR_{i,t}} = S^2_{AR_i}\left(1 + \frac{1}{M_i} + \frac{(R_{m,t} - \overline{R}_m)^2}{\sum_{t=T_0}^{T_1}(R_{m,t} - \overline{R}_m)^2}\right) \tag{21}$$

Where $S^2_{AR_i}$ denotes the unadjusted standard error, M_i denotes the length of the estimation window, while $R_{m,t}$ and $\overline{R}_m$ denotes the market return at time=t in the estimation window and mean of the market return in the estimation window, respectively.

We aggregate the SARs, and use the following test statistic for $\overline{AR}$:

$$z_{patell_i} = \frac{\overline{SAR}_t}{S_{\overline{SAR}_t}} \tag{22}$$

Where $S_{\overline{SAR}_t}$ is calculated using $S^2_{ASAR_t} = \sum_{i=1}^{N} \frac{M_i-2}{M_i-4}$, where M_i denotes the length of the estimation window.

We use the following test statistic for $\overline{CAR}$:

$$z_{patell} = \frac{1}{\sqrt{N}} \sum_{i=1}^{N} \frac{CSAR_i}{S_{CSAR_i}} \tag{23}$$

Where $CSAR_i$ is the cumulative $SAR_{i,t}$ during the event window. $S^2_{CSAR_i}$ is calculated using $S^2_{CSAR_i} = L_2\frac{M_i-2}{M_i-4}$, where L_2 denotes the length of the event window.

A1.3 Standardized Cross-sectional test (BMP)

Boehmer et al (1991) further proposed a standardized cross-sectional test that is robust for event-induced variance. They conclude that other tests result in rejection of the null hypothesis too frequently (Boehmer et al., 1991), as the event might cause significant variance uptick in the event-observations. Boehmer et al. (1991) introduce this test as an extension of the traditional cross-sectional test, including elements from the above-mentioned Patell test. The proposed test include data from both the estimation window and the event window, and the researchers argue that this test is more robust than previous methods as it is sufficient even though there is volatility induced by the event (Boehmer et al., 1991).

We first test for H_0 that $\overline{AR} = 0$. We use the test statistic:

$$Z_t = \sqrt{N}\frac{\overline{SAR_t}}{\sqrt{var(\overline{SAR_t})}} \tag{24}$$

With corresponding variance:

$$var(\overline{SAR_t}) = \frac{1}{N-1}\sum_{i=1}^{N}(SAR_{i,t} - \overline{SAR_t})^2 \tag{25}$$

To test the H_0 if $\overline{CAR} = 0$ with the BMP-test, we use the formula:

$$z_{BMP} = \sqrt{N}\frac{\overline{SCAR}}{S_{\overline{CAR}}} \tag{26}$$

Where the $SCAR$ is the standardized cumulative abnormal return for each event, while the $\overline{SCAR_i}$ is the average $SCAR_i$ for all i.

A1.4 Non-parametric tests

We also include a non-parametric test to supplement the other tests and ensure robustness. The Wilcoxon rank test acts as a supplement to the conventional t-test. The test considers both the size and the magnitude of the abnormal returns. It further assumes that none of the abnormal returns are equal and non-zero. We let:

$$W_t = \sum_{i=1}^{N} rank(AR_{i,t}) \tag{27}$$

Where $rank(AR_{i,t})$ is the rank of the absolute value of $AR_{i,t}$. The test statistic is further calculated as follows:

$$z_{wilcoxon,t} = \frac{W - N(N-1)/4}{\sqrt{(N(N+1)(2N+1)/12)}} \tag{28}$$

A2 Use of proceeds examples

Table A2.1: Examples of stated intended use of proceeds

Observation ID	Issuer	Announcement date	Use of proceeds category	Use of proceeds collected from Newsweb
46	Scatec Solar	13.06.2018	Investment	The net proceeds from the Private Placement will be used to accelerate growth, including near term equity investments in large scale solar projects, beyond the 1.1 GW currently under construction.
129	Opera Software	26.06.2014	Investment	The purpose of the placement is to strengthen the Company´s capital base for current and future strategic acquisition activities
157	Scana Industrier	29.01.2013	General	The net proceeds to the Company from the Private Placement will be used for strengthening of the balance sheet and general corporate purposes.
216	Codfarmers	24.06.2010	General	The net proceeds from the Private Placement and the Havlandet Share Issue will be used for biomass growth and general corporate purposes.
247	Kongsberg Automotive	01.09.2009	Recapitalisation	Through the successful completion of the private placement Kongsberg Automotive has reached an important milestone in the restructuring of the company
282	Songa Offshore	16.10.2008	Recapitalisation	The purpose of the private placement is to finance the Company's short term liquidity requirements, including debt repayment, cash calls from total return swaps and increase in Company's cash holdings.

Note: The table presents examples of the *ex ante* stated intended use of proceeds.

A3 Correlation Matrix

Table A3.1: Correlation matrix between explanatory variables, M&A

	High Abn. Search	Multiple Bidders	Foreign Acquirer	Rel. Deal-Size	Ln (MCap)	Ln (B2M)	Ln(Turn -over)	Leve -rage	ROA
High Abn. Search	1.000								
Multiple Bidders	0.043	1.000							
Foreign Acquirer	0.076	−0.109	1.000						
Rel. Deal-Size	0.094	0.173	0.242	1.000					
Ln(MCap)	0.110	−0.019	−0.141	0.064	1.000				
Ln(B2M)	0.129	0.040	0.074	−0.257	-0.334	1.000			
Ln(Turnover)	0.179	0.031	0.024	0.085	0.210	−0.181	1.000		
Leverage	0.125	0.076	−0.030	−0.067	-0.002	0.029	0.128	1.000	
ROA	−0.027	0.103	−0.211	0.025	0.391	−0.241	−0.047	0.039	1.000

Note: The table presents a correlation matrix of the explanatory variables from the cross-sectional regression on M&A pre-announcement $\overline{CAR}$ in the interval [-13,-1]

Table A3.2: Correlation matrix between explanatory variables, *Recapitalisation*

	High abn. Search	Accel -erated	Rel. Deal-Size	Ln (MCap)	Ln (B2M)	Ln(Turn -over)	Leve -rage	ROA
High Abn. Search	1.000							
Accelerated	−0.009	1.000						
Rel. Deal-Size	0.089	−0.005	1.000					
Ln(MCap)	0.130	0.123	−0.301	1.000				
Ln(B2M)	−0.100	0.123	0.202	−0.086	1.000			
Ln(Turnover)	0.051	0.225	−0.048	0.320	0.122	1.000		
Leverage	0.058	0.136	0.161	−0.018	0.182	0.050	1.000	
ROA	0.209	0.043	−0.306	0.276	−0.144	0.014	−0.128	1.000

Note: The table presents a correlation matrix of the explanatory variables from the cross-sectional regression on Recapitalisation pre-announcement [-25,-1].

A4 List of *noisy* observations

Table A4.1: List of *Noisy* observations

***Noisy* observations**

M&A	*Recapitalisation*
Evry	Hurtigruten
Expert	Norwegian Air Shuttle
Hurtigruten	XXL
NextGenTel	
Spectrum	
Stavanger Aftenblad	
Synnøve Finden	
Tandberg	
Tide	

Note: The table provides an overview of the companies evaluated as noisy. There are 9- and 3 unique companies removed in the M&A- and Recapitalisation sample, respectively. A total of 12 and 4 observations are removed in the two samples as some of the companies are included more than once.

A5 One-Factor Model Versus Fama-French Three-Factor model

Table A5.1: One-Factor Model vs. Fama-French three Factor

M&A				Investment			
Day	Average Abnormal Return (%)			Day	Average Abnormal Return (%)		
	One-Factor Model	Fama-French 3-factor model	Two Sample t-test		One-Factor Model	Fama-French 3-factor model	Two Sample t-test
-25	0.05	-0.06	0.29	-25	-0.28	-0.33	0.11
-24	-0.39	-0.41	0.03	-24	0.27	0.33	-0.11
-23	-0.07	-0.21	0.30	-23	0.36	0.26	0.24
-22	-0.02	-0.03	0.02	-22	0.36	0.31	0.12
-21	-0.32	-0.50	0.36	-21	-0.32	-0.33	0.00
-20	-0.22	-0.13	-0.22	-20	0.21	0.16	0.18
-19	-0.14	-0.14	0.00	-19	0.21	0.16	0.14
-18	0.34	0.25	0.24	-18	0.05	0.11	-0.13
-17	0.18	0.00	0.46	-17	-0.21	-0.23	0.05
-16	-0.05	-0.13	0.19	-16	-0.33	-0.31	-0.04
-15	0.58	0.59	-0.02	-15	0.02	0.02	-0.01
-14	-0.49	-0.49	0.00	-14	-0.22	-0.19	-0.06
-13	0.05	-0.02	0.12	-13	0.18	0.07	0.24
-12	0.72	0.72	-0.01	-12	-0.06	-0.14	0.13
-11	0.47	0.39	0.16	-11	1.02	1.05	-0.04
-10	0.40	0.49	-0.19	-10	-0.26	-0.23	-0.05
-9	-0.18	-0.13	-0.12	-9	0.52	0.51	0.02
-8	0.08	-0.02	0.26	-8	0.53	0.55	-0.03
-7	0.64	0.61	0.07	-7	0.32	0.27	0.08
-6	-0.24	-0.23	-0.04	-6	0.14	0.09	0.10
-5	0.00	0.04	-0.11	-5	0.62	0.74	-0.22
-4	0.59	0.43	0.38	-4	-0.27	-0.26	-0.02
-3	0.82	0.79	0.05	-3	0.56	0.46	0.20
-2	0.46	0.44	0.05	-2	0.10	0.13	-0.07
-1	0.94	0.86	0.20	-1	0.49	0.49	0.01
0	15.10	15.08	0.01	0	0.97	0.82	0.08
1	1.23	1.18	0.08	1	-2.54	-2.50	-0.03

Note: The table provides a comparison of average abnormal returns using the One-factor- and the Fama-French 3-Factor Model for the *M&A* and *Investment* samples. There is also provided a two-sample t-statistic to check if the difference between the average abnormal returns equal zero.

Table A5.2: One-Factor Model vs. Fama-French three Factor

General				Recapitalisation			
Day	Average Abnormal Return (%)			Day	Average Abnormal Return (%)		
	One-Factor Model	Fama-French 3-factor model	Two Sample t-test		One-Factor Model	Fama-French 3-factor model	Two Sample t-test
-25	1.55	1.58	-0.02	-25	-1.43	-1.59	0.13
-24	-0.17	-0.11	-0.07	-24	1.10	1.08	0.02
-23	0.72	0.75	-0.04	-23	-0.11	0.06	-0.24
-22	0.82	0.82	-0.01	-22	-1.02	-1.00	-0.02
-21	0.39	0.50	-0.17	-21	-0.41	-0.22	-0.24
-20	0.60	0.47	0.17	-20	-0.25	-0.20	-0.05
-19	0.28	0.21	0.12	-19	0.67	0.67	0.00
-18	0.07	0.07	0.01	-18	-0.67	-0.69	0.02
-17	0.28	0.21	0.12	-17	-0.90	-0.85	-0.05
-16	0.14	0.08	0.07	-16	-0.28	-0.39	0.12
-15	0.91	0.87	0.06	-15	0.07	0.09	-0.02
-14	-0.51	-0.58	0.14	-14	0.50	0.39	0.08
-13	0.58	0.64	-0.09	-13	-0.32	-0.15	-0.12
-12	-0.55	-0.53	-0.03	-12	-1.16	-1.32	0.14
-11	-0.56	-0.44	-0.22	-11	-0.33	-0.28	-0.04
-10	0.17	0.26	-0.19	-10	-0.40	-0.36	-0.04
-9	0.08	0.15	-0.11	-9	-0.35	-0.32	-0.03
-8	1.03	0.98	0.07	-8	-0.88	-0.86	-0.02
-7	0.47	0.59	-0.14	-7	-0.29	-0.45	0.17
-6	0.07	0.02	0.08	-6	0.11	0.24	-0.15
-5	0.05	-0.06	0.11	-5	-0.46	-0.34	-0.15
-4	0.04	0.11	-0.08	-4	-0.29	-0.25	-0.04
-3	-0.37	-0.37	0.00	-3	-0.64	-0.96	0.34
-2	0.23	0.15	0.18	-2	-1.44	-1.26	-0.14
-1	0.20	0.24	-0.06	-1	0.09	0.12	-0.03
0	-0.64	-0.74	0.06	0	-11.55	-11.66	0.02
1	-3.56	-3.60	0.03	1	-2.49	-2.49	0.00

Note: The table provides a comparison of average abnormal returns using the One-factor- and the Fama-French 3-Factor Model for the *General* and *Recapitalisation* samples. There is also provided a two-sample t-statistic to check if the difference between the average abnomal returns equal zero.