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Decoding Insider Trades

An empirical analysis of how the Swedish stock market reacts to insider trading activity

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Abstract

In our study we explore and analyze 6 627 insider trades made on the NASDAQ OMX Stockholm between 2010 and 2014. We ask if publicly available information on insider trading can give insight into where stock prices will head in the future and if outside investors can earn abnormal returns by creating portfolios based on such information. We conduct our research using the event-study methodology as described by MacKinlay (1997) and show that insiders are better informed about the overall future performance of their company, indicating a violation of the semi-strong form market efficiency hypothesis. We show that different firm characteristics such as market capitalization, financial leverage and industry, together with individual characteristics such as insider type and traded volume, can emphasize differences in abnormal returns following insider trades. Based on our findings we create three rule-based insider portfolios. We show that we are able to gain risk-adjusted returns above the market, but when controlling for transaction costs the risk-adjusted return vanish. Our study has implications for market efficiency and offers important insights for those who seek to earn higher returns by following strategies based on the publication of insider trades.

Preface

Our interest in both the theoretical and practical aspects of the financial markets has evolved throughout our five years of study. We therefore wanted to choose a topic that had profound theoretical concepts, as well as being practically feasible.

Our motivation to study reported insider trades originated from the insider portfolio and weekly insider article in the Norwegian financial newspaper, *Finansavisen*, as well as the investment strategy of the asset management firm, *Dovre Forvaltning*. Drawing inspiration from courses such as Corporate Finance, Investments and Asset Management at NHH we decided to analyze the theoretical implications and practical inference of reported insider trades.

Throughout the process, we have been able to apply knowledge obtained through our studies at NHH. In addition, we have gained significant knowledge about insider trading, market efficiency, event methodology and data analysis, to mention some.

We would like to express our utmost gratitude towards our supervisor, Associate Professor Trond M. Døskeland. His guidance through selecting our course of study and structuring the thesis proved to be critical for the final product. He gave constructive feedback and challenged us at being independent, something that provided us with important insights and a considerable learning outcome.

Further, we would like to thank *Dovre Forvaltning*, represented by Kęstutis Baltakys, for inspirational inputs in regards to the hypotheses and for providing us with extensive raw data material.

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Contents

1. Introduction

In our study we seek to explore and analyze 6 627 insider trades made on the NASDAQ OMX Stockholm[1] between 2010 and 2014. The purpose is to address the following:

Can publicly available information on insider trading give insight into where stock prices will head in the future?

and

Can investors ("outsiders") earn abnormal returns by creating portfolios based on such information?

What is Insider Trading?

Insider trading is a term that most people associate with illegal conduct. This is a common misconception as the term includes both legal and illegal conduct. Insider trading is simply the trading of stocks, bonds, stock options or other financial securities of a public company by individuals within the firm. These individuals are, when meeting certain criteria, called *insiders*.

An insider is legally permitted to trade shares and other securities of his own company when not based on *inside information* and when the trading activity is properly reported to the respective financial supervisory authority. Inside information, or private information, can be defined as non-public and material information. It is precise information that can affect stock price movements significantly and that when traded upon can mitigate investment risk and provide returns above what a typical investor could achieve. Both insiders and outsiders of the company can hold inside information and trading on such information for profit is illegal.

Insiders may have several motives for trading their company's securities when not holding inside information. One can assume that the company board of directors, its management and employees have more knowledge of future prospects and projects in their company and the industry it operates within, and trade based on the assumption that the company's value is different from the current consensus of the market (profit motive). It is also recognized in literature (e.g. Huddart and Ke, 2007; Ke et al., 2003; Seyhun, 1998) that insiders trade for

[1] Also referred to as the Stockholm Stock Exchange or *Stockholmsbörsen*

other reasons than profit, such as the need for liquidity (liquidity motive) or to better diversify their holdings and re-balance their portfolio (diversification motive). Tax motives may also explain some of the insider trading behavior, for example by realizing losses by the end of year to gain from tax benefits. Stock awards and the granting of options by the company to its insiders are examples of compensation that will be reported as insider trades (external motive). Lastly, insiders might be motivated to illegally exploit inside information by trading on this information or to manipulate market prices for personal gains (manipulation motive).

We find it reasonable to believe that insider trading activity can signal where a company's stock will head in the future and therefore potentially lead to superior returns. We do not consider if the insider trade is legally or illegally conducted, nor if the insider herself profits from the trade. We want to know if one, as outsiders, can profit from the signal the publication of an insider trade sends to the market and if this signal is handled in an efficient and unbiased way by the market participants. Findings corroborative of our research questions will indicate a violation of the semi-strong form market efficiency hypothesis.

Motivation and Structure

Our motivation to study reported insider trades originated from the insider portfolio and weekly insider article in the Norwegian financial newspaper, *Finansavisen*, as well as an interest in the investment strategy of the asset management firm, *Dovre Forvaltning*. We chose the Swedish stock market over the Norwegian stock market as there are approximately four times more reported insider trades in the first market during the period of interest, providing more data to analyze.

We will look into the role of information in financial markets and introduce theory on market efficiency in Chapter 2. In Chapter 3, existing literature on insider trading will be introduced together with our proposed hypotheses. In Chapter 4, we will introduce the Swedish stock market and give the reader a description of the data analyzed. In Chapter 5 we will discuss and decide how to perform the analysis, before presenting and discussing the results in Chapter 6. Based on our findings, we will create three rule-based insider portfolios to see if outsiders can make risk-adjusted profit by following such strategies in real life. These portfolios, the method for testing them and their results, are presented in Chapter 7. Finally, in Chapter 8 we will present our conclusions.

2. Market Efficiency

2.1 Information

The overall purpose of a financial market is to facilitate the transfer of funds between investors and borrowers. A well-functioning financial market acts as a lubricant for the economy and enables efficiency in terms of consumption smoothing and optimal allocation through time. To determine to which extent a financial market is well functioning, three criteria's must be met. First, the financial market is said to be a *complete market* if all the assets or contracts needed to fulfill the demand of its participants exists. Secondly, when the costs of conducting these trades are reasonably low, the market is *operationally efficient*. Thirdly, if all available information concerning fundamental values are present, the financial market is ***informationally efficient***.

In an efficient market, all past and present information is reflected in asset prices and prices become non-predictable (random). This "random walk" of the prices results in the failure of any investment strategy that aims to beat the marked consistently over time. The concept of gaining from trading on the information extracted from the publication of insider trades relies on the foundation that not all information is present in the markets. This implies that the financial market is not informationally efficient and that insiders hold information or knowledge concerning fundamental values, future prospects or the general state of a company that affect security prices. To further elaborate on the concept of informational efficient markets, we will present the renowned Efficient Market Hypothesis (EMH) as presented by Eugene Fama in his ground-breaking article *«Efficient Capital Markets: A Review of Theory and Empirical Work»*, in May 1970.

2.1.1 Market Efficiency

«An efficient capital market is a market that is efficient in processing information»

(Fama, 1976, p. 133)

Fama developed a framework for describing to which degree markets are efficient. The Efficient Market Hypothesis (EMH) states that markets are efficient when prices reflect all relevant information at any point in time. The concepts of information and time required further detailing and thus Fama defined three forms of information efficiency: weak, semi-strong and strong form market efficiency. Each form of efficiency is defined with respect to the information that is reflected in prices. The EMH is illustrated in Figure 1 below.

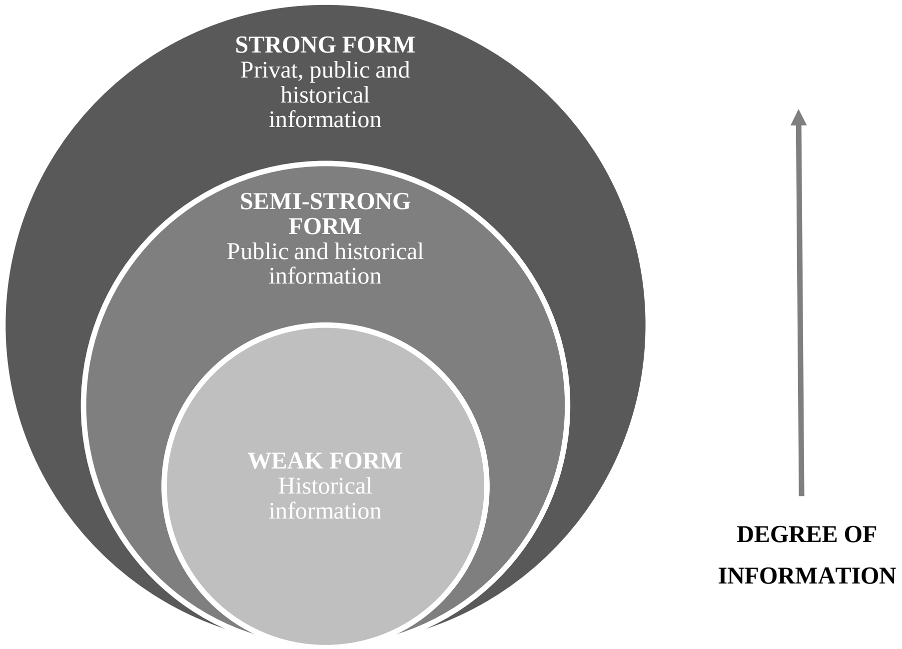

Figure 1 - Efficient Market Hypothesis

Weak Form

The first form of market efficiency Fama described is weak form efficiency. If all past market data is reflected in the security prices, the market is weak form efficient. This means that one cannot make abnormal risk-adjusted returns by using historical price and volume data to predict future price changes. Technical analysts do not think the stock market is weak form efficient, but believes that investors are emotionally driven and predictable. They believe this predictability is exploitable and shows in past prices and volume data.

To determine whether markets are weak form efficient one can study patterns in historical prices. Statistical studies can reveal serial correlation in security returns and thereby reveal patterns. Poterba and Summers (1987) presented evidence that stock returns exhibit positive serial correlation in the short term and negative serial correlation in the long run, known as mean reversion. De Bondt and Thaler (1985) created “winner” and “loser” portfolios based on 36 months performance and tracked the portfolios performance against a benchmark for three years. They showed that the “losers” consistently beat the benchmark and the “winners” underperformed – indicating that “winners” would become “losers” and vica versa. Much like De Bondt and Thaler, Jegadeesh and Titman (1993) documents that strategies which buy stocks that have performed well the past 6-months and sell stocks that have performed poorly the past 6-months, generate significant positive returns over holding periods of three to twelve month, providing evidence against weak-form market efficiency. Brock, Lakonishok and LeBaron (1992) demonstrates that a simple set of technical trading rules over a sample period shows significant forecast power for changes in the Dow Jones Industrial Average.

Although these studies present evidence against weak-form market efficiency, most studies indicate that investors cannot consistently earn abnormal profits using historical price information, nor using technical analysis, in developed financial markets (e.g. Bessembinder and Chan, 1998; Jensen and Benington, 1970; Fama and Blume, 1966). Bessembinder and Chan (1998) shows that with the inclusion of trading costs, technical strategies does not show evidence indicative of market inefficiencies.

Semi-Strong Form

When all publicly known and available information is reflected in the security prices, the market is semi-strong efficient. Publicly available information includes for example financial statements (e.g. firm’s interim reports), announcements (e.g. contract signings, interest rate decisions and insider trades) and market data (e.g. stock prices, currency rates and employment numbers). The implication of semi-strong efficiency is that analysis of publicly available information has no value.

Neither technical nor fundamental analysis can be used to achieve abnormal returns as all information is reflected in the security prices If a market is semi-strong efficient, it must also be weak form efficient. Information in reported insider trades has no value if the market is semi-strong form efficient.

Fundamental analysts believe that publicly available information can be used to identify firms that deviate from their true and fair value to achieve abnormal risk-adjusted returns. The common methods for testing if markets are semi-strong efficient is to perform an event study of investors’ reactions to information releases, to do long-run abnormal return studies or to look for market anomalies. Most studies do not conclude that there are profit opportunities. Keown and Pinkerton (1981) identified 194 firms that were take-over targets in a merger and looked for abnormal returns following the takeover announcement. No excess returns were found. Other studies that support the semi-strong form of the EMH includes studies related to corporate reorganizations and stock splits (Fama, Fisher, Jensen and Roll, 1969).

Although most violations of the semi-strong form market efficiency are found to be more subtle and temporary, there are some exceptions. Bernard and Thomas (1989) looked at quarterly earnings surprises. They defined a surprise as the difference between the actual quarterly earnings announcement and the forecasted earnings and found that large surprises lead to higher positive abnormal return. They also found “drift” in the returns, as the upward trend (drift) in the stock price following a positive earnings surprise continues for a couple of months after the earning announcement. The same goes for negative earnings surprises. Loughran and Ritter (1995) show that returns following IPOs and seasoned equity offerings underperform over moderately long time periods. Ikenberry, Lakonishok and Vermaelen (1995) show evidence of positive long-run abnormal risk-adjusted returns following share repurchases; Michaely, Thaler and Womack (1995) find the same for dividend initiations. Dividend omissions have the opposite effect (negative long-run abnormal risk-adjusted returns).

Also some “anomalies” are found as evidence against semi-strong (and weak form) EMH. Banz (1981) show that small cap stocks have positive alphas, and that most of the abnormal returns occur in January[2]. Fama and French (1992) find that value companies (stocks with high book-to-market ratios) have higher CAPM adjusted returns than portfolios of growth stocks (low book-to-market ratios)[3].

Strong Form

In a strong form efficient market also private information is reflected in security prices. If the market is strong form efficient, it must also be weak and semi-strong form efficient.

In the case of a strong-form efficient market, what is classified illegal insider trading would not yield abnormal returns. Neither would any other trading done by individuals with private information. An example of this might be company managers trading on information related to their company’s financial condition, before these conditions are publicly released[4].

To test whether a market is strong form efficient, we have to test if an investor can earn an abnormal return by trading on private information. Many studies have found that strong-

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[2] Chen and Singal (2004) indicate that the most obvious reason for this effect is tax-loss selling.

[3] Fama and French (1993) introduces their 3-factor model, including size and book-to-market factors.

[4] Trading on private information is illegal in most countries.

form efficiency does not hold and that trading on private information is profitable, including Jaffe (1974) and Rozeff and Zaman (1988).

Further Implications

The EMH has been tested on numerous occasions throughout the years in relation to insider trading, most prominently by Jaffe (1974) and Eckbo (1998), with diverging conclusions. The fact that different studies provide different conclusions may be an indication that the market may be exploitable and not entirely efficient. In Chapter 3, we will elaborate further on previous research on insider trading.

Using publicly announced information from *Finansinspektionen*, the Swedish Financial Supervisory Authority, our hypotheses will put the **semi-strong form market efficiency** to the test. Findings suggesting that investors can consistently earn abnormal returns by trading based on reported insider trades may be evidence contrary to semi-strong form market efficiency and will test the capability of the market to incorporate the reporting of insider trades in the security prices.

2.1.2 Asymmetric Information

An informationally efficient market as presented by Fama depends on an even distribution of information among the market participants. If insiders, or any other market participant, hold "superior" information that can lead to the gain of abnormal returns; information is in fact not evenly distributed. We have *asymmetric information*.

It is common to refer to two types of asymmetric information: Adverse selection and moral hazard.

Adverse Selection

Taking advantage of asymmetric information *before* a transaction takes place is known as *adverse selection*. A situation where buyers have more information than sellers (or vica versa) about some aspect of a trade is an example of adverse selection.

The expression originated in the insurance business as a consequence of high-risk individuals (dangerous jobs, high-risk lifestyle, history of illness) buying life insurance. The high-risk individuals demand for insurance were found to be positively correlated with the individual's risk of loss, likely caused by the private information only known to the individuals (Polborn, Hoy, Sadanand, 2006). Another example is the *lemons problem*[5], popularized by George Akerlof in 1970. Akerlof demonstrates adverse selection through the example of dealing used cars, were the seller has more information than the buyer about the used car's condition.

In the financial markets, adverse selection relates to insider trading. An insider holding inside information has superior information compared to other market participants and adverse selection arises if the insider takes advantage of this information.

Moral Hazard

Taking advantage of asymmetric information *after* a transaction has taken place is known as *moral hazard*. Moral hazard arises when a risk-taking party to a transaction knows more about her intentions than the party paying the consequences of the risk.

[5] Defective cars were known as *lemons* in the marketplace

An example may be a large shareholder and manager in a financial distressed company taking on additional risk to boost earnings on the expense of debt holders (has exposure to the downside). An insider that holds stock options in the company can enter into risky ventures to increase share price on the expense of debt holders.

The theory of asymmetric information is crucial to support our hypothesis that portfolios based on insider trades can earn abnormal profits. In the introduction, we state that it is reasonable to assume that the company board of directors, its management and employees have more knowledge about future prospects and projects in their company and the industry it operates within, and that insider trading activity can signal where a company’s stock is heading. When disregarding what moral grounds the insiders may have to perform the trades, and whether or not the information is legal, that insiders can possess superior information may suggest the finding of abnormal returns following insider trades.

2.2 Regulation

To ensure an even distribution of information and prevent the problems associated with asymmetric information, markets are regulated. In the following, we will discuss existing regulation on insider trading. This will give important background information for the rest of the thesis and enhance our understanding of who company insiders are, what inside information is and how it is regulated.

Do we need Insider Trading Laws and Regulation?
Bhattacharya and Daouk (2002) did a study of 103 countries with an active stock market, and found that insider laws exist in 87 of them, but enforcement by prosecutions has taken place in only 38 of them. Before 1990, insider laws existed in only 34 countries, and enforcement was found in 9 of them. To prove the presence of illegal insider trading is difficult. Trading securities as an insider is a legal activity and is prohibited only if the trader possesses inside information. Physical evidence is rare and evidence must build on the examination of innocuous events such as trading patterns and relationship and meetings between people. This makes it difficult to conclude that illegal insider trading has occurred. Most successful prosecutions build on rare cases of cooperating witness testimony or direct confession.

There are many arguments not to regulate and prohibit insider trading: It is extremely hard to monitor asymmetrical information – What people know and do not know – and one should therefore not spend resources on enforcing insider trading laws and regulation as it is not cost effective. When comparing insider trading to other economic crimes there are no “real” victims, with the possible exception of other shareholders. It does not harm the society in the same manner as other crime such as embezzlement, tax fraud, client fraud or corruption. Others see insider trading as a form of compensation and benefit for corporate employees that can permit lower salaries, which in turn benefit investors. Manne (1968) argues that insider trading does not injure the shareholders and that insider trading is the only practical and appropriate method available for compensating innovators, by promising huge rewards.

These arguments are countered by the fact that it leads to an incentive for corporate insiders to enter into risky ventures for short-term personal gains and that gains are captured at the expense of other shareholders. Allowing insider trading will weaken investor’s confidence in the capital markets, and make capital less available. One need investors to trust the markets to be fair. Researchers also seem to find evidence that insider trading laws matter to stock market development. Beny (2005) find that countries with stricter and more developed insider trading laws tend to have more diverse equity ownership, more accurate stock prices and more liquid markets. Bainbridge (2000) argues that firms should be the ones profiting from information value, and not the firm's insiders. Illegal insider trading can therefore be thought of as theft of property rights.

Global Insider Laws

Laws and regulation on insider trading vary significantly from country to country and enforcement is mixed. In the United States, illegal insider trading refers to

> *buying or selling a security in breach of a fiduciary duty or other relationship of trust and confidence, while in possession of material, nonpublic information about the security. Insider trading violations may also include "tipping" such information, securities trading by the person "tipped," and securities trading by those who misappropriate such information* [6]

Corporate insiders and beneficial owners of more than 10 % of a class of the company's equity securities were first regulated under the Securities Exchange Act of 1934. Most of the development in the law prohibiting insider trades are based on court rulings were the courts have exercised authority based on the contents from section 16(b) and section 10(b) in this Act[7]. In August 2002, the SEC implemented the provisions of the Sarbanes-Oxley Act (SOX) of 2002, accelerating the deadline for filing most insider ownership reports[8]. The Sarbanes-Oxley act was passed by the US Congress to improve corporations' financial disclosure and prevent accounting fraud after seeing the need for an overhaul of regulatory standards after the Enron, WorldCom and Tycon scandals in the early 2000s.

Together with the rest of the world, Europe was having virtually unregulated markets for insider trading until the European Community Directive Coordinating Regulations on Insider

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[6] U.S Securities and Exchange Commission | Insider Trading. 2015. Available at: http://www.sec.gov/answers/insider.htm. Accessed 01 April 2015.

[7] After the US stock market crash of 1929, the Congress enacted the Securities Act of 1933 and the Securities Exchange Act of 1934 to control the abuses believed to have caused the crash.

[8] U.S Securities and Exchange Commission | Insider Trading. 2015. Available at: http://www.sec.gov/answers/insider.htm. Accessed 01 April 2015.

Trading (The EC Directive) was adopted on November 13^{th} 1989. The EC Directive defines inside information in article 1 as information of *«a precise nature»* about a security or issuer which has not been made public and which if made public «*would likely have a significant effect on the price*» of the security. In articles 2 and 3, the directive prohibits insiders from taking advantage of inside information, also by tipping or using others. The EC directive is today part of the European Economic Area Agreement (EEA) between the EU member states and Iceland, Lichtenstein and Norway. In 2003, after the implementation of the Sarbanes-Oxley Act in the US in 2002, the European Parliament adopted the stricter Market Abuse Directive (2003/6/EC). This was done to increase investor confidence through preventing market abuse such as insider trading and preserving a smooth functioning of European Financial Markets. The countries in the EEA agreement are obliged to abide by the law, but are allowed through article 6 in the EC Directive to adopt stricter regulations. The Scandinavian countries generally have stricter regulation than those imposed by the EU. Norway is known as a country with especially strict regulation and consequences of breaching the rules.

In sum, there are substantial differences in regulations on insider trading. These differences relates to the definition of an insider, how insider trading is regulated and how it is enforced.

Swedish Insider Laws

In Sweden, *Finansinspektionen* (the Swedish Financial Supervisory Authority) supervises insider trading. It was established in 1991 as part of the Swedish Ministry of Finance with the aim of creating a single integrated regulator covering the Swedish financial industry. *Finansinspektionen* authorize, supervise and monitor all companies within the Swedish financial markets.

Swedish limited companies listed on an exchange or authorized marketplace are obligated to report the identity of persons in the company and its subsidiaries that hold insider positions. In «*The Act concerning Reporting Obligations for Certain Holdings of Financial Instruments (2000:1087*)» people that hold insider positions are defined as:

1. *A **member** or **alternate member** of the company's or its parent company's board of directors*
2. *A **managing director** or **deputy managing director** of the company or its parent company*
3. *An **auditor** or **deputy auditor** of the company or its parent company*

4. *A* ***partner*** *in a partnership that is the company's parent company, though not a limited partner*
5. *A holder of an* ***other senior executive post*** *or* ***qualified function*** *of a permanent nature at the company or its parent company, if the post or function can normally be considered to have access to non-public information on circumstances that may affect the company's share price*
6. *A* ***holder of a senior executive post*** *or a* ***service provider*** *in accordance with points 1-3 and 5 above* ***in a subsidiary*** *if they may normally be considered to have access to non-public information which may affect the company's share price*
7. ***Larger shareholders*** *who themselves, together with one or more natural or legal persons in concert or through a company, own at least ten per cent of the share capital or number of votes for all shares in the company*

Closely related parties of persons with an insider position, both physical persons and legal entities, are covered by the reporting obligations too. This includes spouses, cohabitees, children, other closely related parties and legal persons whose activities are significantly influence by the person with an insider position.

Insiders regulated by the Swedish Financial Supervisory Authority must report their holdings of shares and changes in their holdings within five trading days of the trade taking place (Norway: no later than the start of trading on the following day). There is also a general ban on trading in the 30 days prior to the publishing of interim reports, including the day of publication (Norway: 1 month prior to interim reports, 2 months prior to annual report). This is examples of Swedish (Norwegian) regulations that are more stringent than imposed by the EEA Agreement. The difference in the speed of reporting is likely to have an effect on the size of the abnormal returns measured around the reporting date, as we expect insider trades with stricter reporting (closer to the trade) to be more informative. The Swedish Financial Supervisory Authority updates its public insider register, *insynsregisteret*, every day after the stock market opening hours, normally at 5:30pm.

The regulations mentioned above are regulations as of June 2015. The last changes to these regulations were made July 1, 2005. Pre 2005, insiders could not sell any position in securities within three months from the purchase date. Since our analysis starts in 2010, this will not affect the signal of the insider trade.

3. Existing Literature and Hypotheses

With a good understanding of asymmetric information, insider trading and insider regulation, relevant existing literature were studied, and we found numerous cases that provided important insights on the theoretical and practical aspects of insider trading. These studies, although often diverging in their conclusions, offers noteworthy inferences on the significance of insider returns. In this section, we will present our hypotheses and compare with previous published literature.

We have defined three levels to classify the applicable literature and test our hypotheses on: (1) Market level, (2) Firm level and (3) Individual level, starting on the market level. Determining if there exist abnormal returns resulting from reported insider trading on a market level sets the premise for more detailed testing on the firm and individual level.

The hypotheses are constructed as alternative statements that will assist us in capturing the essence of abnormal returns following the publication of insider trades. The testing framework will be presented in Chapter 5, and the null hypotheses will be tested and discussed in Chapter 6.

3.1 Market level

The market's reaction to new information is dependent upon the ability of the market to process and reflect the information efficiently, as described in Chapter 2. As we believe that insider trades may serve as indicators for abnormal returns, we assume that insiders have an informational advantage. However, previous literature on the presence of abnormal returns from insider trades has mixed conclusions.

All Trades

In one of the earliest relatable studies, Glass (1966) found it reasonable to assume that insider trades serve as a useful indicator of short-term stock performance. Givoly and Palmon (1985) show that the abnormal returns subsequent to insider trades in fact are separable and substantially higher than normal return for other events such as firm specific news or events. Seyhun (1992) find that insiders purchase stocks prior to an abnormal price increases and sell stocks prior to an abnormal decline in prices. Cohen, Malloy and Pomorski (2012) find evidence of a rise in abnormal returns following the first six months after an insider trade, followed by stagnation with no sign of reversion. They propose that this stagnation is a sign that the emerged information has a permanent effect on the company´s value. Others suggest that the rapid rise in the initial months indicates that insiders is better to predict values in the near future and not necessarily in the long run (Jaffe, 1974; Rogoff, 1964). Omsted and Olsen (2014) document in their dissertation on insider trades on the Norwegian Stock Exchange (*Oslo Børs*) a strong initial market reaction to insider trades and evidence of long-term market outperformance for some data subsets. Husøy and Jentoft (2013) find the same. These studies serve to indicate abnormal returns subsequent insider trades, and thereby reject the EMH in a semi-strong form.

Performing similar analysis on the Oslo Stock Exchange, Engevik and Helleren (2009) and Holen (2008) found evidence that insiders gain abnormal returns, but are careful suggesting that outsiders can profit from these trades. Eckbo et al (1998) applied three different measures of performance[9] on the Oslo Stock Exchange. They find zero or negative abnormal

[9] (1) Using portfolio aggregation - Aggregating insider stock holdings each month, akin to an insider fund, and track the performance of "the fund". (2) A conditional portfolio benchmark return approach. (3) A conditional portfolio weight measure

performance by insiders. They suggest this may come from very strict regulations on insider trades in the Norwegian market, or that the results may be a special case for small and concentrated markets, characterized by high variance in returns and strong correlation across securities. These studies serve to prove the EMH in a semi-strong form.

In the Swedish market, Sjöholm and Skoog (2006) performed an analysis on insider trades during 1990-2004 and found that both buy and sell transactions provided abnormal returns for both short and long horizons. Sjöholm and Skoog (2006, pp. 11-12) write that the same was found by Hjertstedt et al (2000) for the period 1996-1999. Further, they write that Hjemgård et al (2002), performing similar studies between 1998-2002, did not find evidence on insiders earning abnormal profits. This was also the conclusion of the studies performed by Heinonen et al (2002).

Postulating that abnormal returns subsequent the publication of insider trades exist, we will try to determine to which extent and over which period. As the Swedish insider trades are published after the stock market opening hours, the stock price should, in a perfectly efficient market, adjust before the stock market opens the following day. The return the following day is our 1-day (1D) return measure. In addition to testing for 1-day, we will test for holding periods of 20, 40, 60 and 120 trading days following the insider trade[10]. Based on previous literature, we expect to observe a mean reversion tendency preceded by an early peak in abnormal returns.

- **Hypothesis 1.1 - Insiders on the Stockholm Stock Exchange earn abnormal returns on *all trades* after 1 day and 1, 2, 3 and 6 months following the publication of insider trades**

[10] Our analysis will measure abnormal returns for every trading day between 1 and 120 trading days following the event. 1-day, 1-month (20 trading days), 2-months (40 trading days), 3-months (60 trading days) and 6-months (120 trading days) is chosen for illustrational purposes only.

Purchases and Sales[11]

Investigating the distinction between returns from insider purchases and insider sales can highlight the predictive powers of insider trades towards both positive and negative development in stock returns. Previous research indicates that purchases provide higher abnormal returns than sales (Johansson et al, 2005; Jeng et al, 2003; Lakonishok and Lee, 2001). The simple explanation is that sale of capital is more related to a liquidity motive than a profit motive. There may also be a moral dilemma associated with selling/short-selling your company's stock.

To examine the market's ability to absorb information on insider purchases and insider sales, we propose the following hypotheses:

- **Hypothesis 1.2 - Insiders on the Stockholm Stock Exchange earn abnormal returns on *purchases* after 1 day and 1, 2, 3 and 6 months following the publication of insider trades**

- **Hypothesis 1.3 - Insiders on the Stockholm Stock Exchange earn abnormal returns on *sales* after 1 day and 1, 2, 3 and 6 months following the publication of insider trades**

[11] Sales include both reducing current stock holding and short-selling a stock

3.2 Firm level

The process of segregating securities into categories by capitalization, industry, leverage and growth prospects is a common approach for any investor to facilitate informed and diversified investments. Applying several firm level criteria, we will investigate whether we find variations in abnormal returns.

Market Capitalization

Former research indicates that insider trading in small cap firms earn significantly higher abnormal returns than insider trading in other firms. Seyhun (1986) regresses insiders' abnormal profits on firm size and shows that there is a negative correlation between insiders' abnormal return and firm size. Lakonishok and Lee (2001) support this conclusion. When investigating the usefulness of insiders' activities in timing the market, they point out that insiders in small cap companies have a relative advantage in timing over insiders in large cap companies, resulting in higher abnormal returns. Hjertstedt et al (2000), referred to by Sjöholm and Skoog (2006, p. 12), shows that insider transactions done in smaller firms are more profitable than those in larger firms for the Swedish market. Johansson et al (2005) supports this, finding that abnormal returns following insider purchases were more significant for smaller companies.

Small cap companies usually have fewer employees, less shareholders and less analyst coverage than large companies, suggesting that information is less distributed. This can in turn create potential advantages for more informed insiders. We believe that this information asymmetry can provide higher abnormal returns for small cap firms[12] and propose to examine this through assessment of the following hypothesis:

- **Hypothesis 2.1 – Insider trades in small cap companies provide a stronger signal of abnormal returns than mid and large cap companies**

[12] Firm size (small, medium or large) is given by NASDAQ OMX Stockholm's designation.

Growth vs Value Firms

The P/E (Price-Earnings) ratio quantifies the relationship between the stock price and the earnings of a company and is used in our study to identify companies with growth opportunities. As stock prices reflect what investors believe a company is worth, P/E can be seen as a reflection of the markets expectation on the firm's growth prospects. Growth companies usually have high P/E values due to a large present value of growth opportunities implicit in the price (increasing price) combined with low earnings (expected to rise in the future). Value companies tend to have lower P/E because these companies tend to have less growth prospects and pay dividends (suppressing price). This leads to higher (and more stable) earnings relative to price.

In an efficient market, the present value of growth opportunities should be reflected in asset prices. Jeng et al (2003) tested a hypothesis that the highest insider profits occur for firms with low book-to-market (BM) ratios. Although not significant, their results suggest that insiders in low-BM (growth) firms earn higher profits than insiders in high-BM firms (value). Similarly, Aboody and Lev (2000) find that insider gains are higher in high-R&D firms (growth) than those in low-R&D firms (value). The intuition is that high-R&D serves as a signal of asymmetrical information and potential for an informational advantage by insiders. Omsted and Olsen (2014) found, contrary to the other literature, that insiders in value firms earn highly significant abnormal returns 1 to 3 months following the insider trade, before the returns seem to stabilize. For growth firms, they do not find any significant results for any horizon.

We postulate that growth opportunities are first and best signaled by insiders and hypothesize that insiders possess more knowledge of the value of their company's growth opportunities, and are able to gain abnormal returns on this informational advantage.

- **Hypothesis 2.2 – Growth companies earn a significant higher abnormal return than value companies following the publication of insider trades**

Growth companies will be classified as companies in our dataset with high P/E ratios (4th quartile) and value companies as those with low P/E (1st quartile).

Firm Leverage

In their renowned paper, Miller and Modigliani (1958) presented pioneering theories on capital structure. They proposed that in a perfect capital market, the total value of a firm is not affected by its choice of capital structure. We believe that testing for differences in capital structure is interesting as high leverage can create potential opportunities and incentives for moral hazard (excessive risk-taking) or adverse selection (sensitive information is worth more in highly leveraged and more volatile stocks).

The debt-equity (D/E) ratio is our chosen measurement of financial leverage. This is a common and easily interpreted ratio used to assess a firm's extent of debt as a source of financing. A higher ratio means higher debt financing. Fidrmuc et al (2006) found that purchases in financially distressed firms provide a stronger signal of abnormal returns than purchases in firms that are not in financial distress. Even though firms with high leverage not necessarily are in financial distress, we expect that when an insider trades in a leveraged company the abnormal returns will be magnified relative to when an insider trades in a company with low financial leverage. We propose the following hypothesis:

- **Hypothesis 2.3 – Insider trades in companies with high financial leverage earn significant higher abnormal returns than companies with low financial leverage following the publication of insider trades**

Companies with D/E ratios in the 4th quartile will be classified as highly leveraged firms, and companies in the 1st quartile as firms with low leverage.

Firm Industry

It is well known that different industries exhibit different characteristics. This can be differences in ownership structure, financial structure, growth opportunities, sensitivity to economic conditions or consumer behavior. Employees may possess expertise and first hand knowledge about the industry they work in, but lack expertise in a different industry. In addition, there may exist natural or regulatory barriers between industries and the outside, potentially leading to difficulties for outside investors to fully comprehend the mechanisms and volatility of that industry. This may cause one industry to be more exposed to asymmetric information than another.

Seyhun (1998) tested for correlation between insider trading in companies in the same industry. In his example, he finds evidence of strong positive correlation between insider trading in the automobile industry. He finds that by aggregating insider trading across companies in the same industry, other motives (such as liquidity motives) may be eliminated. An insider aggregation thus serves to reinforce the information and signal of insider trades, resulting in higher profitability. This study sets the foundation for our hypothesis that there are informational differences between industries. In a relatable study on the Norwegian stock market, Husøy and Jentoft (2013) found evidence of abnormal returns following the publication of insider trades in the Oil & Gas, Consumer Goods, Health Care, Industrials and ICT sector. Although using a slightly different industry classification[13], the abnormal returns are highest within the health care industry. This is interesting, as it makes sense to assume that information from complex and heavily regulated industries such as health care may be difficult for outside investors to fully comprehend.

- **Hypothesis 2.4 – There is a difference in abnormal returns across industries[14]**

[13] Using the Global Industry Classification Standard (GICS), developed by MSCI and Standard & Poor's.

[14] We divided firms into ten industries using the ICB (Industry Classification Benchmark) by the FTSE group

Firm Reporting

As quarterly firm reports contain a considerable amount of information, one can assume that outsiders gain information and strengthen their knowledge of a company's business when these reports are published. Due to a narrower informational gap between insiders and outsiders close to the reporting date, we believe that insider trades made adjacent to quarterly reports gives a weaker signal for abnormal returns following the trade than transactions made *not* adjacent to the quarterly reports.

Kallunki et al (2009) analyses insider trading around quarterly and annual reporting during changing legislative environments in Sweden from 1980 to 2003 (legislation getting stricter). They conclude that as insider legislation becomes tighter, insiders trade more carefully, especially before the earnings announcements. They also find some opportunistic behavior among insiders, showing that they are reluctant to sell stocks before positive earnings announcement. Kolasinski and Li (2010) found that insiders are buying (selling) after good (bad) earnings announcements, when the price reaction to the quarterly reported earnings is low (high). They further demonstrated that insiders trading in response to quarterly reporting and the price reaction to the publishing of these reports generate abnormal returns.

We believe that after the publication of a quarterly report, returns from insider trades will be weaker as the informational gap between insiders and outsiders are narrower. We want to put this to the test by proposing the following hypothesis:

- **Hypothesis 2.5 – Insider trades adjacent to quarterly reports provide a weaker signal of abnormal returns than trades not adjacent to quarterly reports**

Trades adjacent to quarterly reports are all trades performed in the months *following* the quarterly reporting months, i.e. May (Q1), August (Q2), November (Q3) and February (Q4). Trades not adjacent to quarterly reports are the other eight months.

Momentum

Momentum can be defined as the rate of acceleration of a stock's price (or other factor, such as volume). A momentum strategy is based on the premise that a stock which has performed good (poor) in the past will continue to perform good (poor) in the future.

Although a momentum strategy does not rely on any fundamental values and is considered a technical strategy, it has some statistical foundations. Poterba and Summers (1987) found evidence that stock returns are positively serially correlated over short horizons (momentum) and negatively auto-correlated over long horizons (mean reversion). Jegadeesh and Titman (1993) document that strategies of buying stocks that have performed well the past 6-months and selling stocks that have performed poorly the past 6-months generate significant positive returns over holding periods of three to twelve month. Seyhun (1998) shows that stock prices exhibit positive momentum at horizons up to one year; that winners outperform the market index and losers continue to underperform.

In the case of insiders, Seyhun (1998) found that they tend to sell past winners and buy past losers. This suggests that insiders are not motivated by momentum strategies, but exhibit rather contrarian behavior when investing. These findings hold for both short horizons, up to one year, as well as for long horizons, up to five years. That insiders are contrarian is supported by Lakonishok and Lee (2001).

In this hypothesis, we want to investigate all reported insider trades regardless of whether the trade is a purchase or a sale. By including all trades, we account for all possible investment strategies of an insider. We believe that there may exist a synergy effect when an insider trade is reported in a company with momentum. When a stock has a positive (negative) momentum, an insider purchase may act as a continuation of this momentum providing additional positive (negative) returns. On the other hand, we also believe that an insider trade can signal a reversal of the momentum, i.e. a purchase (sale) might signal the termination of a negative (positive) momentum. It is therefore in our belief that insider trades performed in companies with a momentum signals stronger abnormal returns following the event.

- **Hypothesis 2.6 – Insider trades in companies with momentum earn a significant higher abnormal return following the trade than insider trades in companies without momentum**

To segregate insider trades with and without momentum, we had to examine the returns of the traded stock prior to the insider trade taking place. We ranked all the stocks by their return 120 trading days prior to the trade, and classified insider trades with momentum as insider trades done in the 4^{th} quartile of returns (highest returns; positive momentum) and insider trades in the 1^{st} quartile (lowest return; negative momentum). All other trades were classified as trades without momentum (2^{nd} and 3^{rd} quartile).

3.3 Individual level

This third and final section of the chapter is discussing the characteristics of reported insider trades on an individual level. By taking advantage of the information in the reported insider trades data from the Swedish Financial Supervisory Authority, we are able to look at factors such as the insider's position and trade volume.

Insider Position

The first and most evident individual characteristic from the reporting is the position of the insider. Numerous sources explore the characteristics of the insider's position in the company. While Jaffe (1974) analyzed the number and quantities of different insider types, other studies provide statistical evidence that different insider types possess more valuable information (Seyhun, 1986; Cohen, Malloy and Pomorski, 2012). The consensus indicates that mid-level officers earn the largest returns. Omsted and Olsen (2014) concluded that different insiders on the Oslo Stock Exchange earn different abnormal returns. They found that managers[15] and board members earned the highest abnormal returns.

We suggest that because top management (board members and managing directors) are under scrutiny from regulators and media, they will choose their insiders trades with caution. To comply with political considerations these trades will be more of a routine character, and motivated by diversification rather than chasing abnormal profits. This may not be the case for low profile insiders. In addition, as different insider positions are exposed to different parts of the company's operations, informational asymmetry may arise. Based on evidence from previous research and our reasoning we propose that insiders with different position earn different returns, and we expect to find that low profile insiders earn larger abnormal returns than high profile insiders do.

- **Hypothesis 3.1 – There is a difference in abnormal returns across insiders with different firm positions**

[15] All managers that are not CEO or CFO

Trade Volume

Another interesting characteristics of the reported data is the traded volume. In this hypothesis we will investigate if the reported insider trade volume, in both absolute and relative terms, can predict abnormal returns.

Rationally, a large volume transaction would indicate a strong belief in the stock purchased. This is supported by Seyhun (1986), who finds that insiders will increase their trade volume when they have more valuable information. Contrary to this conclusion, Jaffe (1974) fails to find a relationship between trade size and information value. Also, Barclay and Warner (1993) find that the largest abnormal returns results from medium sized trades. Their estimations indicates that 82.9% of the cumulative price change stems from medium sized insider trades. Omsted and Olsen (2014) find that higher trade volumes seem to yield higher subsequent abnormal returns than lower volume trades. Looking at relative trade volumes, they find significant differences in all models. This is not the case for absolute trade volumes, were they do not find any significant differences in abnormal returns.

As mentioned under insider type, we expect that low profile insiders earn larger abnormal returns than high profile insiders. Similarly, we believe that large absolute volume trades are under higher scrutiny and therefore will include other motives than pure profit.

As our data does not enable us to correct for wealth when looking at trade volumes, it is important to stress the fact that only looking at absolute volumes would discriminate low profile insiders[16]. We therefore also look relative trade volumes. We believe that insiders' willingness to invest correlates with their confidence in the company and that the confidence can be measured by the relative size of their trade. Higher confidence, and therefore higher relative trade volume, should result in higher abnormal return following the trade. We propose to evaluate the following hypotheses:

- **Hypothesis 3.2 – Small *absolute volume* insider trades provide a stronger signal of abnormal returns than large *absolute volume* insider trades**

[16] We find it reasonable to assume that these insiders have less disposable income and wealth than high profiled insiders such as managing directors and parent firm board members.

- **Hypothesis 3.3 – Large *relative volume* insider trades provide a stronger signal of abnormal returns than small *relative volume* insider trades**

We have categorized small absolute volume insider trades as trades with an absolute volume in the 1st quartile of all traded volumes. Large absolute volume insider trades are those in the 4th quartile. Similarly, we have classified small relative volume insider trades with a relative volume in the 1st quartile of all traded relative volumes. Large relative volume insider trades are those in the 4th quartile.

4. Data Description

In this chapter, we describe our data in detail before turning to the method for testing the postulated hypotheses in Chapter 5.

We start by introducing the Swedish Stock Market as a background for understanding the data. Then we describe our raw data and how we cleaned it, before performing a descriptive data analysis.

4.1 The Swedish Stock Market

Nasdaq OMX Stockholm (The Stockholm Stock Exchange or *Stockholmsbörsen*) was founded in 1863 and has been a part of the Nasdaq OMX Group since 2008. It is the primary marketplace for securities in Sweden as well as in the Nordic region. Entering 2015, Nasdaq OMX Stockholm consisted of 307 companies with an average daily turnover of about 10 billion SEK.

Alternative market places like Nasdaq OMX First North, Aktietorget, Alternativa Aktiemarknaden and NGM (Nordic Growth Markets) are also present in Sweden, but these are primarily exchanges for small growth companies.

Nasdaq OMX Stockholm contains a diversified assembly of industries. Whereas the Oslo Stock Exchange is heavily weighted towards oil and shipping companies, Nasdaq OMX Stockholm is more weighted towards industrials which accounts for 27% of the companies on the exchange (Figure 2). Industrials is followed by financials (18%) and health care (13%).

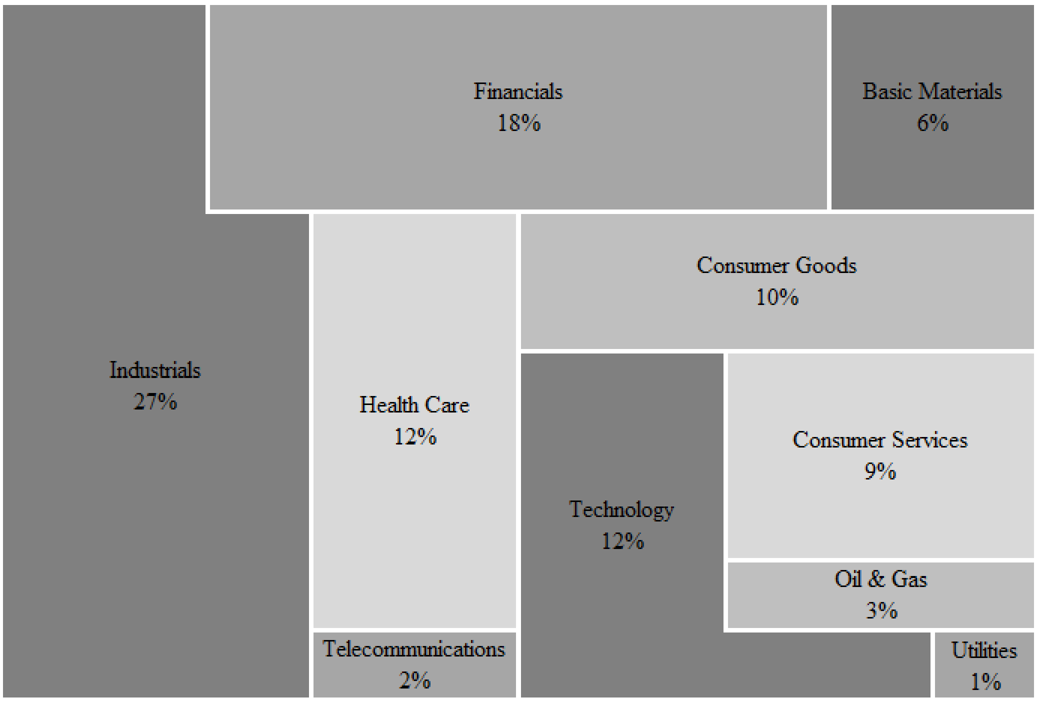

Figure 2 - Industry weight, Nasdaq OMX Stockholm. Source: Swedish Financial Supervisory Authority

What primarily differentiates Nasdaq OMX Stockholm from the other Nordic exchanges is its ownership structure. The exchange is largely dominated by family owned corporations and holding companies. An article from the Swedish weekly business magazine *Affärsvärlden* claims that fifteen families effectively controls 70 % of the stock exchange[17]. This ownership structure has a certain effect on the shares offered on the exchange, resulting in several companies with both common and preferred stocks. This can be seen in contrast to the Oslo Stock Exchange, were most shares are common.

Other large stakeholders on the exchange are foreign owners (improving the competitiveness of the exchange), financial corporations, mutual funds and households. A large foreign investor is the Norwegian Government Pension Fund Global. The fund controls approximately 2% of the shares on Nasdaq OMX Stockholm and has ownership interests in almost 50% of the stocks listed[18].

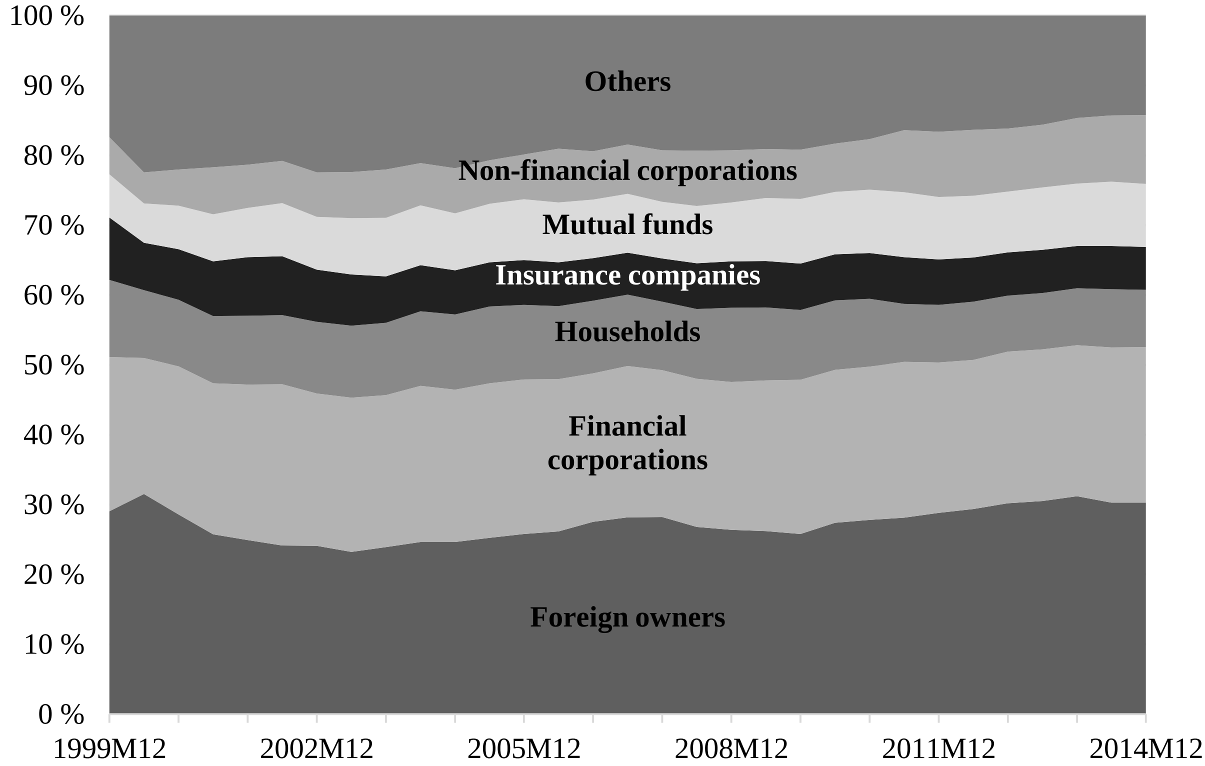

Figure 3 - Ownership structure, Nasdaq OMX Stockholm. Source: Swedish Financial Supervisory Authority

Note that the family owned share of the exchange is dispersed among the different categories. "Others" include central and local governments, banks and credit institutions, non-profit institutions and social security funds.

[17] E24.no | Sveriges mektigste familier. 2015. Available at: http://bit.ly/1FsWGP5. Accessed 13 May 2015

[18] NBIM.no | Holdings. 2015. Available at: http://bit.ly/1NtHIgw. Accessed 13 May 2015

4.2 Raw data

We obtained the raw data from *Dovre Forvaltning*, and it consists of two datasets. The first dataset consist of all insider trades reported to the Swedish Financial Supervisory Authority (*Finansinspektionen*) within the mentioned period, and the data is extracted from their register (*Insynsregisteret*). The number of trades in the raw dataset are 12 127, and includes all trades obliged to be reported according to Swedish insider laws and regulation. The dataset provides information on the date of the insider trade, the date the trade was published, the name of the company traded and it's ticker, the name of the insider and the insider's position within the company, if the trade was a purchase or a sale, what kind of share was traded (Common or preferred share), how many shares were traded, the insiders total holding in the company traded, the price paid and the insider's relative change in the total holding following the trade. A segment of the raw dataset can be found in Appendix A.

The second dataset consist of total return data[19] of all Swedish stocks listed on the OMX Stockholm from 1986 until the end of September 2014. The data is extracted from Macrobond and a segment of the total return data can be found in Appendix B.

[19] Total return includes interest, capital gains, dividends and distributions realized over the period and gives a measurement of the actual rate of return for a given security.

4.3 Data Cleaning and treatment

We have chosen to use all companies listed on Nasdaq OMX Stockholm for our analysis. Swedish companies listed on other stock exchanges such as Nasdaq OMX First North, Aktietorget, Alternativa Aktiemarknaden and NGM (Nordic Growth Markets) have been removed from our dataset. We have excluded the securities from the other stock exchanges, as some of them are not supervised by *Finansinspektionen*, due to varying degree of liquidity and the need for another benchmark.

Insider trades in equity other than A (Voting shares) and B shares (Non-voting shares) have been removed. This includes trades in firm options, warrants or other derivatives and firm bonds, convertible debt and other debt securities.

Insider trades made on the same day by the same insiders have been aggregated. E.g. if an insider buys 15 000 shares and then 5 000 shares on the same day, this is seen as one trade of 20 000 shares. If an insider buys and sells the same amount of shares on the same day, this will be seen as a trade of 0 shares (the trade is disregarded).

Insider trades done by the company itself (share repurchase) and by relatives of the insider, such as spouses and children, were excluded as our goal is to look at the signal sent by the publication of insider trades made by individuals *within* the firm.

After cleaning the data, 6 699 insider trades were left for analysis.

When we calculated normal returns using our chosen asset pricing models[20], data was missing during the 120 trading days prior to the event (the insider trade) taking place (estimation window) or in the 120 trading days following the event taking place (event window) for a few events. This can be due to bankruptcy, liquidation, mergers or acquisitions of the companies. Because of this, another 72 trades were removed, resulting in a final number of 6 627 insider trades to analyze in 238 different companies; an average of ~33 trades per company.

An excerpt from the cleaned and treated data can be found in Appendix C.

[20] More on this in Chapter 5 – Method.

4.4 Descriptive Data Analysis

			Transaction value					
Transaction	**#**	**%**	**Median**	**Mean**	**25 %**	**75 %**	**Min**	**Max (mSEK)**
Purchase	4 479	68 %	236 013	16 487 851	74 866	1 149 942	172	4 339
Sale	2 148	32 %	683 708	24 056 316	180 253	2 845 780	34	6 708
All transactions	6 627	100 %	337 297	18 939 870	94 605	1 752 749		

Table 1 - Distribution of insider trades by transaction type and traded value

As shown by Table 1, 4 479 (68%) of the insider trades were purchases and 2 148 (32%) were sales. The mean transaction value among all transaction was 18 939 870 SEK. The distribution is positively skewed by a number of extreme outliers, and we can observe a much lower median of 337 297 SEK. Also the 3rd quartile numbers, with transaction values ≥ 1 752 749 SEK, is way lower than the mean. The maximum transaction value in our dataset is 6 708 million SEK, and the lowest is 34 SEK.

In general, sales have a higher transaction value than purchases. We believe this can be explained by different motives when selling as opposed to purchasing. Many insiders' purchases both opportunistically and by routine over time in smaller blocks, before selling it all off in one large block to realize gains, meet tax claims or for other liquidity needs.

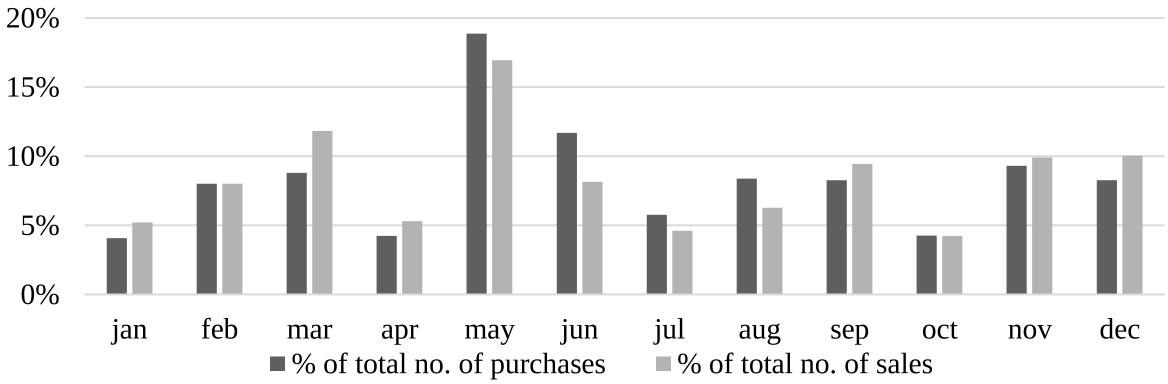

Figure 4 - Distribution of insider trades by transaction type and month

When looking at the distribution of insider trades over the different months for the years 2010-2014, we observe one clear tendency. Most companies file their quarterly earnings report in January (Q4, year before), April (Q1), July (Q2) and October (Q3) and the number of insider trades are at their lowest in these months. Remembering from Swedish insider laws and regulation, Swedish insiders are banned from trading 30 days prior to the publishing of interim reports, including the day of the publication. From the monthly distribution, we observe that the total number of both purchases and sales is highest in May, with 19% of all purchases and 17% of all sales.

Insider Position

Different types of insiders exist. Based on the available data, we have divided insiders into three categories. (1) Primary insiders - Individuals that have a direct legal relationship with the company traded, such as executives, board members, alternate board members, large shareholders and partners. (2) Secondary insiders - Individuals in an indirect relationship with the company traded, for example children or spouses. (3) Insiders that are not individuals, e.g. the company itself, the parent company or any company subsidiary. As mentioned, our objective is to look at the signal sent by the publication of insider trades made by individuals within the firm, therefore only primary insiders are of interest in this analysis.

We have categorized our primary insiders into the following six categories: (1) Managing Director, (2) Board member parent firm, (3) Alternate and/or subsidiary board member, (4) Large shareholder, (5) Other executive and (6) Other position. The number indicates the priority of which category the insider is put in. Many of our insiders have more than one role, e.g. the insider might be both managing director (MD), board member in the parent company and a large shareholder. This particular insider will be classified as (1) Managing Director. Another insider, which is both a large shareholder and has another executive role, will be classified as (4) Large shareholder. The logic behind the classification is the expectancy of the insider’s knowledge of the company and the probability of having asymmetric information. Please consult Appendix D for details.

			Transaction value				
Primary Insider	**#**	**%**	**Median**	**Mean**	**25 %**	**75 %**	**Max (mSEK)**
Managing Director	662	10 %	501 118	17 013 270	137 004	3 186 937	2 894
Board member parent firm	2 008	30 %	504 680	28 927 538	128 036	3 056 592	4 339
Alternate/subsidiary BM	148	2 %	187 504	751 389	58 791	555 153	10
Large shareholder	798	12 %	2 653 903	66 758 979	415 563	12 941 147	6 708
Other executive	475	7 %	254 482	1 250 084	99 954	1 014 445	31
Other position	2 536	38 %	167 301	859 287	61 066	563 377	59
All transactions	6 627	100 %	337 297	18 939 870	94 605	1 752 749	

Table 2 - Distribution of insider trades by insider type and traded value

Apart from Other positions, most trades are done by Board members of the parent firm (30% of all trades), followed by Large shareholders (12%) and Managing Directors (10%). Large shareholders are the ones with the largest transaction value (Median: 2 653 903 SEK), followed by Board members of the parent firm (504 680 SEK) and Managing Directors (501 118 SEK). This seems reasonable from a wealth perspective.

Firm Size

In addition to the data in the raw dataset obtained from *Dovre Forvaltning*, we have added data on firm size, firm industry, debt-to-equity (D/E) ratio and price-earnings (P/E) ratio. This data has been downloaded from Macrobond and Bloomberg.

Firm size are divided into small cap, mid cap and large cap based on their market capitalization (stock price multiplied by the number of shares outstanding). Using NASDAQ OMX Stockholm's designation, we define small cap as companies with a market capitalization below 150 million euro, mid cap as companies with a market capitalization between 150 million and 1 billion euro and large cap as companies with a market capitalization over 1 billion euro.

			Transaction value					
Firm Size	**#**	**%**	**Median**	**Mean**	**25 %**	**75 %**	**Min (SEK)**	**Max (mSEK)**
Small cap	2 275	34 %	192 572	3 880 234	59 481	1 086 997	68	469
Mid cap	2 284	34 %	330 809	8 791 251	101 804	2 084 151	34	2 324
Large cap	2 068	31 %	532 118	46 101 220	158 125	2 372 190	1 146	6 708
All transactions	6 627	100 %	337 297	18 939 870	94 605	1 752 749		

Table 3 - Distribution of insider trades by firm size and traded value

Using NASDAQ OMX Stockholm's designation, we obtain a fairly even distribution of firm sizes. We can see the transaction value increase as the size of the firm increases in Table 3.

Firm Industry

Firms are divided into ten industries using the ICB (Industry Classification Benchmark) maintained by the FTSE group. The ten industries are: Oil & Gas, Basic Materials, Industrials, Consumer Goods, Consumer Services, Health Care, Telecommunications, Utilities, Financials, and Technology.

			Transaction value					
Firm Industry	**#**	**%**	**Median**	**Mean**	**25 %**	**75 %**	**Min (SEK)**	**Max (mSEK)**
Oil & Gas	28	0 %	512 325	19 649 217	307 375	8 666 875	32 480	173
Basic Materials	352	5 %	324 170	35 726 700	100 447	1 580 500	1 005	6 708
Industrials	1 922	29 %	340 504	30 806 782	98 848	2 049 322	193	2 490
Consumer Goods	651	10 %	422 677	11 202 258	129 718	1 382 850	472	2 346
Consumer Services	789	12 %	307 716	19 587 006	103 359	1 975 800	34	2 536
Health Care	556	8 %	115 360	2 925 383	48 353	479 765	260	607
Telecommunications	257	4 %	159 545	960 503	77 869	623 761	2 606	29.15
Utilities	19	0 %	505 500	1 036 450	50 241	954 445	68	8.35
Financials	1 400	21 %	550 863	17 977 720	129 589	2 666 439	101	4 339
Technology	653	10 %	323 798	5 398 445	77 046	2 123 948	770	660
All transactions	6 627	100 %	337 297	18 939 870	94 605	1 752 749		

Table 4 - Distribution of insider trades by firm industry and traded value

Nasdaq OMX Stockholm is, as mentioned in the introduction to the Swedish stock market, heavily weighted towards industrial and financials and 50% of the total insider trades are within these industries (Table 4).

Price-to-Earnings

P/E is our chosen ratio for identifying companies with growth opportunities. The ratio quantifies the relationship between the stock price and the earnings of a company and is given by the following formula:

$$P/E\ Ratio = \frac{Market\ Capitalization}{Net\ Income} = \frac{Share\ Price}{Earnings\ per\ Share}$$

The P/E ratio can be negative (negative earnings per share). Negative P/E ratios are excluded from our analysis as it will not help us distinguish growth from value companies. Note that the P/E ratio does not take the capital structure of companies into consideration.

We have P/E data on 6 209 out of 6 627 trades.

Debt-to-Equity

D/E is our chosen measure of financial leverage. This is a common and easily interpretable ratio used to assess a firm's extent of debt as a source of financing.

$$D/E\ Ratio = \frac{Short\ Term\ Debt + Long\ Term\ Debt}{Shareholder's\ equity} = \frac{Total\ Debt}{Total\ Equity}$$

We use the market value of equity and debt. Using the book value is not as useful as the interpretation is difficult and the fact that it might be negative will make the ratio useless.

We have D/E data on 3 759 out of 6 627 trades[21].

			Price-Earnings Ratio (P/E)						Debt-Equity Ratio (D/E)			
Firm Size	**#**	**%**	**Median**	**Mean**	**25 %**	**75 %**	**#**	**%**	**Median**	**Mean**	**25 %**	**75 %**
Small cap	2 069	33 %	18.1	30.4	11.2	29.6	232	6 %	1.7	1.8	1.1	2.4
Mid cap	2 178	35 %	16.4	27.1	11.8	22.9	1 617	43 %	1.4	4.3	0.9	2.0
Large cap	1 962	32 %	14.2	19.7	10.3	19.5	1 910	51 %	1.6	4.2	1.1	2.9
All transactions	6 209	100 %	15.9	25.9	11.0	23.4	3 759	100 %	1.5	4.1	1.0	2.3

Table 5 - P/E and D/E ratio for firm size

[21] Due to an error when extracting D/E data, we lost D/E observations in many small cap firms. See Table 5.

As we would expect, small cap companies have the highest median P/E ratio (Table 5). This is most likely caused by the fact that small companies often are growth companies, and/or have more growth prospects than larger companies. This is also seen in the D/E ratio, were small cap companies has the highest leverage. These companies are often dependent on (risky) debt to finance expansions and investments more than larger companies.

Note that the means are positively skewed by extreme outliers.

			Price-Earnings Ratio (P/E)						Debt-Equity Ratio (D/E)			
Firm Industry	**#**	**%**	**Median**	**Mean**	**25 %**	**75 %**	**#**	**%**	**Median**	**Mean**	**25 %**	**75 %**
Oil & Gas	24	0 %	26.9	26.0	7.1	38.6	13	0 %	1.7	1.6	1.5	1.7
Basic Materials	263	4 %	16.0	33.8	11.0	27.8	190	5 %	1.5	1.7	1.0	2.4
Industrials	1 804	29 %	15.5	26.1	11.4	21.8	1 001	27 %	1.8	2.0	1.4	2.7
Consumer Goods	607	10 %	18.3	32.2	14.0	31.1	449	12 %	1.3	0.9	1.2	1.7
Consumer Services	781	13 %	16.7	28.6	12.2	21.1	572	15 %	1.2	1.4	0.9	1.6
Health Care	424	7 %	28.0	46.8	16.8	64.3	139	4 %	0.7	1.0	0.5	1.5
Telecommunications	227	4 %	15.8	22.4	10.0	33.4	185	5 %	1.1	1.1	0.9	1.2
Utilities	12	0 %	32.4	34.5	23.1	38.7	19	1 %	1.5	1.4	1.0	1.6
Financials	1 459	23 %	11.1	14.2	7.0	16.5	1 055	28 %	2.1	10.6	0.7	21.4
Technology	608	10 %	18.6	24.2	14.3	24.0	136	4 %	0.9	0.9	0.8	1.0
All transactions	6 209	100 %	15.9	25.9	11.0	23.4	3 759	100 %	1.5	4.1	1.0	2.3

Table 6 - P/E and D/E ratio for firm industry

Looking at the P/E and D/E ratio for the different firm industries, excluding the industries with very few observations (Oil & Gas and Utilities), we can observe that health care and technology has the highest median P/E ratios in Table 6. Firms within these industries often have huge potential for future earnings represented by a price including these growth opportunities today. Earnings are often suppressed as the technology or drug (or other) are under development and not fully adopted by the market. This leads to a relatively large P/E ratio.

Looking at the D/E ratio in Table 6, we can observe that financials stand out with the highest ratio, followed by industrials. Financial institutions typically borrow money to lend money, while capital-intensive industries utilizes debt as a common practice for financing their assets, leading to higher debt-to-equity than other industries.

Note that the means are positively skewed by extreme outliers.

5. Method

Having stated our hypotheses and prepared the dataset, the next step was to decide how to measure the effects, if any, resulting from publication of insider trades. This part of the thesis is an in-depth discussion and description of how we performed our analysis.

5.1 Theoretical Framework

To look at the ability of outside investors to gain abnormal returns by following insider trade signals, we need a method to measure the effect of these signals. Together with intensive-trading criteria, event studies are suitable for determining the information level of insider trading for future returns. An event study attempts to measure the effect of a catalyst occurrence on a security, and is therefore appropriate when examining whether or not outsiders can earn abnormal returns. Events may be earnings announcements, a company filing for bankruptcy protection or the publication of an insider trade. Previous literature suggest delayed stock price reaction to events such as tender offers (Lakonishok and Vermaelen, 1990), dividend initiations (Michaely, Thaler and Womack, 1995) and mergers (Jensen and Ruback, 1983; Agrawal, Jaffe and Mandelker, 1992), to mention some. An event study can reveal information on how a security reacts to an event, and help to predict how other securities will react to a similar event. The underlying assumption is the efficient market hypothesis (markets are at least semi-strong efficient) and the market should therefore process the (event) information in an efficient and unbiased way.

Intensive-trading criteria methods focus on the abnormal returns to firms in relation to the intensity of insiders' purchases and sales over well-defined periods (Jeng, Metrick, Zeckhauser, 2003). A security may for example be labeled an insider buy for a month if two insiders bought it and no insiders sold it, or a security being net bought by insiders in a given period. These are examples of "intensive-trading" rules. The criteria may vary, but two common features are shared: (1) Abnormal return analysis averages across firms and not trades after classification and (2) the classification of firm uses some filter rule defined over a fixed time period (e.g. 1-month, 6-month, 1-year) were the firms are only reclassified after each period. This means that immediate abnormal returns will not be included in the analysis. In contrast, event studies make it possible to examine short-term and immediate abnormal returns following insider trades publication. This is the reason for choosing the event study methodology over the intensive-trading criteria method(s).

Jeng, Metrick and Zeckhauser (2003) uses a portfolio-based approach by imagining that all insider purchases (or short sales) are placed in a portfolio and held for 6 month, starting the day after the insider trade taking place. The portfolio works like a shadow mutual fund, combining all insiders. The portfolio will be weighted in proportion to the values of the underlying insider trades and the returns on the portfolio will proxy for the value-weighted returns earned by insiders over the holding period. Unfortunately, this method makes it impossible to look at subsequent abnormal returns across trades.

As the event study methodology has the strongest approach when it comes to the short-term window and allows running tests and measure abnormal returns on different data subsets, we decided to conduct an **event-based study[22].**

[22] As the other methodologies, the event study has drawbacks. These are discussed in 6.4 Research Critique.

5.2 Event Study

There are many variations in the application of the event study methodology (e.g. Mitchell and Netter, 1994; MacKinlay, 1997). As there exists no unique structure for an event study, we decided to use the same structure as described by MacKinlay (1997). MacKinlay uses financial market data to measure the impact of a specific event (an earnings announcement) on the value of a firm (change in its stock price), similar to what we will do.

MacKinlay suggests the following procedure:

1. **Event definition:** What is the event of interest, and over which period will the security prices of the firms involved be examined?

2. **Selection criteria:** What firms are included in the study?

3. **Normal and abnormal return measurement:** How should we measure normal and abnormal returns?

4. **Definition of estimation window:** Given the selection of a normal performance model, we need to define the estimation window of normal returns.

5. **Testing framework:** Formulate the econometric design and aggregating the individual securities abnormal returns.

6. **Hypothesis testing:** What are the empirical results and how can they be interpreted?

In the following, this procedure is described in detail.

5.2.1 Event Definition

The event of interest is the publication of the insider trade. This is the day when the market is made aware of the insider trade.

The security prices of the firms involved will be examined over more than one period. We will measure immediate abnormal returns, and abnormal returns 1-month, 2-months, 3-months and 6-months following the publication of the insider trade[23]. The event window will therefore vary between 1, 20, 40, 60 and 120 trading days following this date. To measure the immediate effect, we will look for abnormal returns on the date following the publication of the insider trade as the Swedish Financial Supervisory Authority updates its register (*Insynsregisteret*) every day after the stock market opening hours.

5.2.2 Selection Criteria

We have chosen to use all companies listed on NASDAQ OMX Stockholm for our analysis. The (Market)value-weighted NASDAQ OMX Stockholm All-Share Index will be used to represent the market when estimating normal returns using our chosen model(s).

For more sample characteristics, we refer to 4. Data Description.

5.2.3 Normal and Abnormal Return Measurement

To be able to test for differences in returns caused by insider trades or other events, we need to model the normal return. Normal return is defined as the expected return a security would earn given the event not taking place. Several asset-pricing models (APM) exist. In the following, we will introduce the most known methods for modelling returns and then discuss and determine which model(s) to use.

MacKinlay (1997) loosely groups the number of approaches available to calculate the normal return of a security into statistical and economic models.

[23] Our analysis will measure abnormal returns for every trading day between 1 and 120 trading days following the event. 1-day, 1-month (20 trading days), 2-month (40 trading days), 3-month (60 trading days) and 6-month (120 trading days) is chosen for illustrational purposes only.

Statistical Models

The statistical models follows from statistical assumptions concerning the behavior of asset return. It does not depend on any economic arguments. For these models, we assume that the securities returns are independently and identically distributed (i.i.d) through time. MacKinlay (1997) states that this assumption does not impose any problems in practice as inferences from these models seem robust to deviations from this assumption. Further, he states that one can also modify the statistical framework to deal with serial correlation and heteroskedasticity by using a generalized method-of-moments approach.

The Constant Mean Return Model

Assumes that the mean return of a security is constant over time and that asset returns are normally distributed and errors are i.i.d.

The Market Model

The market model[24] is an application of simple linear regression to portfolio management. It is a practical and useful method as we have just two sources of risk; systematic risk (unanticipated macroeconomic events) and unsystematic risk. The model assumes that asset returns are normally distributed and errors are i.i.d.

In the market model, the market portfolio is the macroeconomic factor and stocks are assumed to have varying degrees of sensitivity to this one factor. In addition, each stock's return is uniquely affected by unsystematic (firm-specific) events uncorrelated across stocks and with the macroeconomic events.

The market model predicts that the expected return on asset *i* depends on the expected return of the market portfolio, $E(R_M)$, the sensitivity of the returns on asset *i* to movements in the market, β_i, and the average return to asset *i* when the market return is zero, α_i. The variance of the returns on asset *i* consists of two components: a systematic component related to the asset's beta, $\beta_i^2\sigma_M^2$, and an unsystematic component related to firm-specific events, σ_ε^2. The covariance between any two stocks is calculated as the product of their betas and the

[24] The market model is a version of the single-index model first suggested by Sharpe (1963). The single-index model propose that all the covariation of stock returns can be explained by one factor, namely "the index". The market model uses a market index as the factor.

variance of the market portfolio. To estimate alpha, beta and the error variance, historical returns for a stock are regressed against corresponding returns for a market index.

Multifactor Models

The market model assumes that returns are explained only by the return on the market portfolio and can therefore be described as a single factor model. Multifactor models assume that asset returns are driven by more than one factor. We generally have three classifications of multifactor models: (1) macroeconomic factor models, (2) fundamental factor models and (3) statistical factor models.

The macroeconomic factor models assume that returns are explained by shocks in macroeconomic risk factors, such as GDP, inflation and interest rates. Fundamental factor models assume that asset returns are explained by firm-specific factors, such as market capitalization, leverage ratio, earnings growth rate, P/E ratio, P/B ratio, while statistical factor models explain returns by using statistical methods.

Macroeconomic and fundamental factor models differ when it comes to sensitivities, interpretation of factors, number of factors and the intercept term. Sensitivities in the fundamental factor model are not regression slope estimates, which is the case for macroeconomic factor models. The fundamental factors are rates of return associated with each factor while macroeconomic factors are surprises. The number of factors is often small in macroeconomic models, as they are intended to represent systematic risk factors. The intercept equals the stock’s expected return for macroeconomic factor models, while the intercept has no economic interpretation in fundamental factor models; it is the intercept necessary to make the unsystematic risk of the asset equal to zero.

Economic Models

The economic models rely on assumptions concerning investors’ behavior in addition to statistical assumptions. Using economic restrictions, we have the opportunity to more precisely calculate normal returns.

CAPM

The Capital Asset Pricing Model (CAPM) is one of the most renowned models in finance. The model describes the relationship we should expect to see between risk and return for individual assets. Specifically, the CAPM provides a way to calculate an asset's expected return (or "required" return) based on its level of systematic risk, as measured by the asset's beta.

The model assumes that all assets are marketable and that the market is perfectly competitive. Investors are price takers and have the same expected return, variance and covariance forecast for all risky assets. There are no frictions to trading, such as transaction or tax related costs. Further, the model assumes that investors can lend and borrow at the risk-free rate (no spread) and that unlimited short-selling is allowed. To create optimal portfolios, investors only need to know expected returns, variances and covariances.

These assumptions imply that all investors identify the same risky tangency portfolio (the market portfolio), and would want to combine this risky portfolio with the risk-free alternative when creating their optimal portfolios. Since all investors hold the same risky portfolio, each asset's weight in the (risky) portfolio must be equal to its share of the total market value of all traded assets. The market does only price systematic risk, measured by beta. The relationship between expected return and systematic risk for all assets, both portfolios and individual assets, is shown by drawing the graph of the CAPM (the security market line).

Arbitrage Pricing Theory (Ross, 1976)

The Arbitrage Pricing Theory (APT) describes the equilibrium relationship between expected returns for well-diversified portfolios and their sources of systematic risk. The CAPM can be seen as restrictive case of the APT in which there is only one risk factor; the systematic (market) risk factor.

The APT assumes that (1) returns are derived from a multifactor model, (2) that unsystematic risk can be completely diversified away, implying that unsystematic risk has zero risk premium, and (3) that asset prices adjust immediately to their equilibrium values, eliminating the existence of arbitrage opportunities. A major weakness of the APT is the lack of clarity when it comes to which risk factors to include in the model. Ross, Chen and Roll (1986) identified surprises in inflation, GNP (indicated by an industrial production index), investor confidence (indicated by changes in default premiums in corporate bonds) and surprises in the yield curve (indicated by shifts) to be significant macroeconomic factors explaining security returns.

APT eliminates some of the biases found in the CAPM (Banz, 1981; Reinganum, 1981), but it is also found to have a minimal advantage over the market model.

APT and macroeconomic/fundamental multifactor models differs as the APT is a cross-sectional equilibrium pricing model explaining the variation across assets expected return during a single time period. Multifactor models explain the variation over time. The APT assumes no arbitrage opportunities; multifactor model factors are identified empirically by looking for variables that best fit the data. The APT intercept is the risk-free rate, as opposed to the asset's expected return in macroeconomic factor models.

Choosing Model(s)

How should we model normal returns in our analysis?

The constant return model is a very simple model and Brown and Warner (1980, 1985) found, by looking at the variance of abnormal returns, that the model yield results similar to more sophisticated models as the variance is not much reduced. However, as the market model removes the portion of the return related to variation in the market's return, it represents a potential improvement over the constant mean return model by reducing the variance of the abnormal return.

Applying multifactor models often have limited gains. The reason is that the explanatory power of additional factors to the market factor is small. Hence, the variance of the abnormal return is not reduced significantly (MacKinlay, 1997). In cases were the sample securities have a common characteristic, such as firm industry or size, the variance reduction may still be significant, and the use of multifactor models warrants consideration.

The CAPM has disputable assumptions (e.g. all assets are marketable and the market is perfectly competitive), but is simple and elegant. The model was commonly used in the 1970s, but later discoveries have found deviations in the model (Banz, 1981; Reinganum, 1981). The deviations have affected the validity of the models results, which have made room for the use of statistical (regression) models for modeling normal returns. APT (Arbitrage Pricing Theory) multifactor models eliminate some of the biases found in the

CAPM, but is also found to have limited value added over the market model (Brown and Weinstein, 1985).

We have chosen to model the normal return using three different models: (1) The market model, (2) the constant mean return model and (3) a multifactor model. The market model and the constant mean return model are selected due to the combination of their practicality and findings suggesting that the advantage of using more sophisticated models are limited. To further validate our findings and increase the robustness of our results, we have decided to model returns using a multifactor model. All models' estimation procedures are described in 5.2.5 Testing Framework.

Measuring Abnormal Returns

Appraisal of the event's impact requires a measure of the abnormal return. Define the normal return as the expected return a security would earn without any event (i.e. publication of an insider trade) taking place, given the asset pricing model (APM) chosen. Abnormal return (AR) is then any return over (or under) the normal return, for a given time period, *t*.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|APM_t) \tag{1.1}$$

5.2.4 Definition of Estimation Window

When defining the estimation window in which to measure the securities normal returns, it is necessary for the securities estimated volatility to be realistic when the event occurs. A too wide window will include the risk that structural changes in the market or the firm will give a biased estimate of volatility. Similarly, short-term effects such as abnormal market movements may bias a too short window. The estimation window should give a true and statistical picture of the relationship between returns to the securities and returns to the OMX Stockholm All-Share Index. MacKinlay (1997) is using both a 120 and a 250-day estimation window prior to the event when describing the event study methodology in his paper. Peterson (1989) states that typical lengths of the estimation window range from 100-300 days.

The most common choice is to use a period prior to the event window as the estimation window. In our study, we estimate the APM's parameters over the 120 trading days (6 months) prior to the event, consistent with the 120 days we look forward in the event window.

Before estimating the APM parameters, we dismiss 10 trading days prior to the publication date of the insider trade to control for confounding events that could lead to bias in the estimation of returns. Five trading days are dismissed to control for possible effects resulting from the time interval between the insider trade and the publication of the trade. Five more trading days are dismissed to control for possible effects resulting from other events such as the release of important firm or industry specific news, interim reports or other announcements leading insiders to trade.

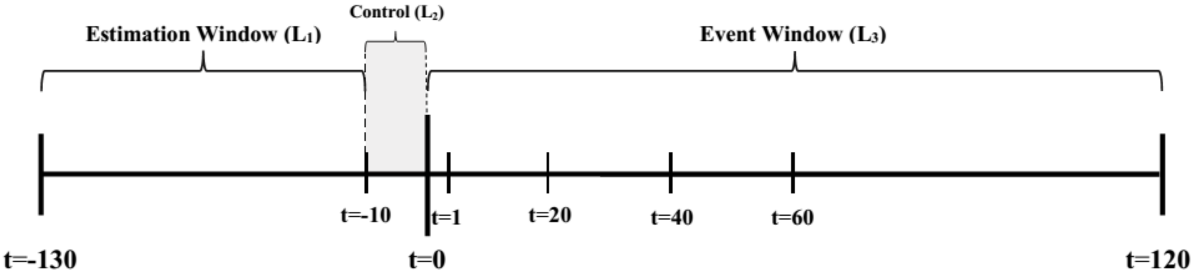

Figure 5 - Estimation and event window

t refers to trading days. $t = 0$ is the event date (the publication date). Length L_1 is the estimation window, length L_2 is the event date including - 10 control days, and length L_3 is the post-event window, or the event window.

The event itself is not included in the estimation period, as the event might influence the APM's parameter estimates. When we have the parameter estimates from the APM's, the abnormal returns can be calculated.

5.2.5 Testing Framework

In the following calculations, all return data are in logarithmic form. The logarithmic returns are calculated as follows:

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \qquad (2.1)$$

Where $P_{i,t}$ represents the security close price on time t

Logarithmic form is beneficial for doing statistical analysis of returns as it yields a distribution that is more compatible with the normality assumptions. The returns are also additive.

Normal Returns

The Market Model

The market model is the regression model often used to estimate betas for common stocks:

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \varepsilon_{i,t} \tag{3.1}$$

where:

$R_{i,t}$ = Return on asset i at time t
$R_{M,t}$ = Return on the market portfolio M at time t
α_i = Intercept (the value of R_i when R_M equals zero)
$\beta_{i,M}$ = Slope (estimate of the systematic risk for asset i)
$\varepsilon_{i,t}$ = Regression error with expected value equal to zero (firm-specific surprises)

The market model makes three assumptions:

1. The expected value of the error term is zero: $E(\varepsilon_{i,t} = 0)$. $Var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon_i}$
2. The errors are uncorrelated with the market return
3. The firm-specific surprises are uncorrelated across assets

This simplifies the estimation procedures needed to conduct the mean-variance analysis.

To estimate the parameters (alpha, beta and the error variance), historical returns for stocks are regressed against corresponding returns for the Nasdaq OMX Stockholm All-Share (market index). The period over which the parameters are estimated is the estimation window (L_1)

The OLS (Ordinary Least Squares) estimators of the market model parameters (alpha, beta and the error variance) are:

$$\widehat{\alpha}_i = \widehat{\mu}_i - \widehat{\beta}_{i,M} \widehat{\mu}_M \tag{3.2}$$

$$\widehat{\beta}_{i,M} = \frac{\sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\mu}_i)(R_{M,t} - \widehat{\mu}_M)}{\sum_{t=t_{-130}}^{t_{-10}} (R_{M,t} - \widehat{\mu}_M)^2} \tag{3.3}$$

$$\widehat{\sigma}^2_{\varepsilon,i} = \frac{1}{L_1 - 2} \sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_{i,M} R_{M,t})^2 \tag{3.4}$$

where

$$\widehat{\mu}_i = \frac{1}{L_1} \sum_{t=t_{-130}}^{t_{-10}} R_{i,t} \qquad (3.5)$$

and

$$\widehat{\mu}_M = \frac{1}{L_1} \sum_{t=t_{-130}}^{t_{-10}} R_{M,t} \qquad (3.6)$$

The Constant Mean Return Model

For each asset *i*, the constant mean return model assumes that returns are given by

$$R_{i,t} = \mu_i + \varepsilon_{i,t} \qquad (4.1)$$

where

$$E(\varepsilon_{i,t}) = 0 \qquad (4.2)$$

and

$$var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon,i} \qquad (4.3)$$

$\hat{\mu}_i$ is estimated by the arithmetic mean of the returns in the chosen estimation-window.

$$\widehat{\mu}_i = \frac{1}{L_1} \sum_{t=t_{-130}}^{t_{-10}} R_{i,t} \qquad (4.4)$$

Where L_i represents the number of trading days in the estimation window (120 days).

The Multifactor Model

Our multifactor model is based on the works of Fama and French (1992, 1993). They find that market variations, firm size and book-to-market equity are factors that explain the cross-sectional average returns in a satisfying manner. These factors will be accounted for by including SMB- and HML factors in addition to the market factor when estimating normal returns.

First, the firms are assigned the label small or big (S and B), based on the median market capitalization. Next, the firms are split into three based on book-market equity. The firms are assigned the label high, medium or low (H, M and L) based on the three breakpoints. Applying the methodology described in Fama and French (1992) we construct six portfolios. The portfolio construction is illustrated in Table 7.

		Market capitalization	
		Small	*Big*
B/M	*High*	Portfolio S/H	Portfolio B/H
	Medium	Portfolio S/M	Portfolio B/M
	Low	Portfolio S/L	Portfolio B/L

Table 7 - Multifactor portfolio construction

For each portfolio the daily value-weighted returns are calculated. The daily SMB factor is found as the difference between the simple average of the three small cap portfolios (S/H, S/M and S/L) and the simple average of the three large cap portfolios (B/H, B/M and B/L). Similarly, the daily HML factor is found as the difference between the simple average of the two high book-to-equity portfolios (S/H and B/H) and the simple average of the two low book-to-equity portfolios (S/L and B/L).

The multifactor model regress the returns on the three factors as:

$$R_{i,t} = \alpha_i + \beta_{i,M}R_{M,t} + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \varepsilon_{i,t} \qquad (5.1)$$

where:

$\beta_{i,SMB} =$ Coefficient for SMB (estimate of the size risk for asset i)
$SMB_t =$ Small Minus Big factor
$\beta_{i,HML} =$ Coefficient for HML (estimate of the value risk for asset i)
$HML_t =$ High Minus Low factor

The expected value of the error term is zero, i.e. $E(\varepsilon_{i,t} = 0)$. $Var\left(\varepsilon_{i,t}\right) = \sigma^2_{\varepsilon_i}$

The additional (as compared to the market model) OLS estimators of the multifactor model parameters are:

$$\widehat{\alpha}_i = \widehat{\mu}_i - \widehat{\beta}_{i,M}\widehat{\mu}_M - \widehat{\beta}_{i,SMB}SMB_t - \widehat{\beta}_{i,HML}HML_t \qquad (5.2)$$

$$\widehat{\beta}_{i,SMB} = \frac{\sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\mu}_i)(SMB_t - \widehat{SMB})}{\sum_{t=t_{-130}}^{t_{-10}} (SMB_t - \widehat{SMB})^2} \qquad (5.3)$$

$$\widehat{\beta}_{i,HML} = \frac{\sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\mu}_i)(HML_t - \widehat{HML})}{\sum_{t=t_{-130}}^{t_{-10}} (HML_t - \widehat{HML})^2} \qquad (5.4)$$

$$\widehat{\sigma}^2_{\varepsilon,i} = \frac{1}{L_1 - 2} \sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_{i,M}R_{M,t} - \widehat{\beta}_{i,SMB}SMB_t - \widehat{\beta}_{i,HML}HML_t)^2 \quad (5.5)$$

Abnormal Returns

Given the different model's parameter estimates, one can measure and analyze the abnormal returns, $AR_{i,t}$, for each firms security in the event window, L_3.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|APM_t) \tag{1.1}$$

For example, when using the market model to measure the normal return, the sample securities abnormal return is

$$AR_{i,t} = R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i R_{M,t} \tag{6.1}$$

The abnormal returns is jointly normally distributed with a zero conditional mean and a conditional variance equal to

$$\sigma^2(AR_{i,t}) = \sigma^2_{\varepsilon,i} + \frac{1}{L_1}\left[1 + \frac{(R_{M,t} - \widehat{\mu}_M)^2}{\widehat{\sigma}^2_M}\right] \tag{6.2}$$

The conditional variance has two components. The first is the disturbance variance, $\sigma^2_{\varepsilon,i}$. The second is additional variance due to the sampling error in α_i and β_i, which leads to serial correlation of the abnormal returns despite the fact that the true disturbances are independent through time. As the estimation window, L_1, gets large, this component will go towards zero as the sampling errors of the parameters cause to disappear. As we use a large estimation window, $\frac{1}{L_1}\left[1 + \frac{(R_{M,t} - \widehat{u}_M)^2}{\widehat{\sigma}^2_M}\right] \sim 0$ and the variance of the abnormal returns can therefore be expressed as:

$$\sigma^2(AR_{i,t}) \cong \sigma^2_{\varepsilon,i} \tag{6.3}$$

Aggregating Abnormal Returns Across Events and Time

Following MacKinlay's approach, we can accumulate abnormal returns across time for an **individual event** by using the cumulative abnormal return (CAR) measure:

$$CAR_{i(t_0,t_1)} = \sum_{t=t_0}^{t_1} AR_{i,t} \tag{7.1}$$

As L_1 increases, the variance of CAR_i is

$$var(CAR_{i,(t_0,t_1)}) = t_1 \times \sigma^2_{\varepsilon,i} \tag{7.2}$$

We get the individual event sample aggregated abnormal returns for each event period, $t = t_0 + 1, t_0 + 20, \dots, t_o + 120$ using the following formula:

$$\overline{AR}_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{7.3}$$

Were N is the number of **events**. The variance (for large L_1) is:

$$var(\overline{AR}_t) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma^2_{\varepsilon,i} \tag{7.4}$$

The abnormal return for any event period can be analyzed using these estimates.

We accumulate abnormal returns across time for **all events** by using the same approach as that used to calculate the CAR measure. For any interval, t, in the event window:

$$\overline{CAR}_{(t_0,t_1)} = \sum_{t=t_0}^{t_1} \overline{AR}_t \tag{7.5}$$

The variance of average cumulative abnormal returns is found as

$$var(\overline{CAR}_{(t_0,t_1)}) = \sum_{t=t_0}^{t_1} var(\overline{AR}_t) \tag{7.6}$$

Statistical Testing and Inference

By assuming that

$$\overline{CAR}_{(t_0,t_1)} \sim N[0, var(\overline{CAR}_{(t_0,t_1)})] \tag{8.1}$$

One can make inferences about the $\overline{CAR}$ and test the null hypothesis that the abnormal returns are zero. This hypothesis can be tested using MacKinlay’s version of the standard t-test:

$$\theta_1 = \frac{\overline{CAR}_{(t_0,t_1)}}{var(\overline{CAR}_{(t_0,t_1)})^{\frac{1}{2}}} \sim N(0,1) \tag{8.2}$$

To test for differences in cumulative abnormal returns for subsets X and Y of the data, we will use Welch's unequal variances t-test for differences in means[25]. The test statistic can, using our notation, be expressed as:

$$t = \frac{(\overline{CAR}_X - \overline{CAR}_Y) - (\mu_X - \mu_Y)}{\sqrt{\frac{var(\overline{CAR}_{X,(t_0,t_1)})}{n_X} + \frac{var(\overline{CAR}_{Y,(t_0,t_1)})}{n_Y}}} \tag{8.3}$$

Variances are assumed unequal for subsets X and Y. μ_X and μ_Y represent the expected cumulative abnormal returns $(E(\mu_X) = E(\mu_Y) = 0)$. n is the number of observations in each subset. The degrees of freedom are calculated using:

$$df = \frac{(\frac{var(\overline{CAR}_X(t_o,t_1))}{n_X} + \frac{var(\overline{CAR}_Y(t_o,t_1))}{n_Y})^2}{\frac{(\frac{var(\overline{CAR}_X(t_0,t_1))}{n_X})^2}{n_X - 1} + \frac{(\frac{var(\overline{CAR}_Y(t_0,t_1))}{n_Y})^2}{n_Y - 1}} \tag{8.4}$$

Our test results are presented in 6. Results.

[25] Welch's unequal variances t-test is chosen over Student's standard two-sided t-test for hypotheses were we apply a two-sided test. Welch’s test is known to be more robust when the samples have unequal variances and unequal sample sizes.

6. Results

This chapter presents the results from testing the postulated hypotheses.

We have chosen to present result statistics for each hypothesis, supplemented with graphical illustrations. The results are then discussed and interpreted in relation to our initial assumptions and previous literature presented in Chapter 3.

We will refer to the cumulative average abnormal return as *highly significant (***)* if it is significant on a 1% level, as *significant (**)* if it is significant on a 5% level and *barely significant (*)* if it is significant on a 10 % level.

Note that we only present results from all our three return models on the market level hypotheses. When doing hypotheses on the firm and individual level, only results from the market model are presented. Any deviations across the models will be commented. We kindly ask to consult Appendix E for complete statistics for all hypotheses. The appendix include the cumulative average abnormal return ($\overline{CAR}$), the standard deviation (σ) and the p-value across our selected horizon and our three respective models. We also include statistics for differences in means.

6.1 Market level

6.1.1 All Trades

Hypothesis 1.1 - Insiders on the Stockholm Stock Exchange earn abnormal returns on *all trades* after 1 day and 1, 2, 3 and 6 months following the publication of insider trades

All trades

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.17 %***	0.028 %	< 0.001	0.18 %***	0.030 %	< 0.001	0.18 %***	0.028 %	< 0.001
1M	0.91 %***	0.124 %	< 0.001	0.83 %***	0.134 %	< 0.001	0.94 %***	0.124 %	< 0.001
2M	1.71 %***	0.175 %	< 0.001	2.07 %***	0.190 %	< 0.001	1.62 %***	0.176 %	< 0.001
3M	2.55 %***	0.215 %	< 0.001	2.81 %***	0.233 %	< 0.001	2.37 %***	0.215 %	< 0.001
6M	4.21 %***	0.304 %	< 0.001	4.91 %***	0.329 %	< 0.001	3.79 %***	0.305 %	< 0.001
n	6627			6627			6627		

Table 8 - Results, all trades. All models

In this hypothesis, we apply our methods on all insider trades in our dataset, both purchases and sales[26]. The results show that the initial market reaction is a highly significant 1-day abnormal return of 0.17%. The $\overline{CAR}$ increases at a higher rate than the standard deviation over the horizon, resulting in highly significant returns over the entire event window. The $\overline{CAR}$ is increasing at a slightly decreasing rate, indicating that the initial effect will diminish over time.

The highly significant results over the horizon indicate that publicly available data on insider trades can predict abnormal returns. We reject the null hypothesis that the $\overline{CAR}$ is equal to zero on all trades for our event window. All our models support this.

[26] Abnormal returns on sales are inverted before aggregating returns to assess the performance of all trades

6.1.2 Purchases

Hypothesis 1.2 - Insiders on the Stockholm Stock Exchange earn abnormal returns on *purchases* after 1 day and 1, 2, 3 and 6 months following the publication of insider trades

Purchases

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.18 %***	0.034 %	< 0.001	0.21 %***	0.037 %	< 0.001	0.19 %***	0.034 %	< 0.001
1M	0.88 %***	0.154 %	< 0.001	0.62 %***	0.167 %	< 0.001	0.90 %***	0.154 %	< 0.001
2M	1.67 %***	0.217 %	< 0.001	1.80 %***	0.236 %	< 0.001	1.58 %***	0.217 %	< 0.001
3M	2.45 %***	0.266 %	< 0.001	2.28 %***	0.290 %	< 0.001	2.40 %***	0.266 %	< 0.001
6M	3.85 %***	0.375 %	< 0.001	3.93 %***	0.409 %	< 0.001	3.49 %***	0.377 %	< 0.001
n	4479			4479			4479		

Table 9 - Results, purchases. All models

In this hypothesis, we analyze the markets overall reaction to reported insider purchases. The results show that the initial market reaction is a highly significant 1-day abnormal return of 0.18%. The $\overline{CAR}$ increases at a higher rate than the standard deviation over the horizon, resulting in highly significant returns over the entire event window. $\overline{CAR}$ is increasing at a higher decreasing rate than for all trades, indicating that the initial effect will diminish slightly faster for purchases alone.

The highly significant results over the horizon and across models indicate that insider purchases signal abnormal returns. We reject the null hypothesis that the $\overline{CAR}$ is equal to zero on purchases over time. All our models support this.

6.1.3 Sales

Hypothesis 1.3 - Insiders on the Stockholm Stock Exchange earn abnormal returns on *sales* after 1 day and 1, 2, 3 and 6 months following the publication of insider trades

Sales

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	-0.15 %***	0.047 %	0.002	-0.12 %**	0.050 %	0.016	0.16 %***	0.047 %	< 0.001
1M	-0.99 %***	0.210 %	< 0.001	-1.27 %***	0.225 %	< 0.001	1.01 %***	0.211 %	< 0.001
2M	-1.77 %***	0.296 %	< 0.001	-2.63 %***	0.318 %	< 0.001	1.71 %***	0.298 %	< 0.001
3M	-2.75 %***	0.363 %	< 0.001	-3.92 %***	0.390 %	< 0.001	2.31 %***	0.365 %	< 0.001
6M	-4.97 %***	0.513 %	< 0.001	-6.96 %***	0.551 %	< 0.001	4.42 %***	0.517 %	< 0.001
n	2148			2148			2148		

Table 10 - Results, sales. All models

In the final market level hypothesis, we analyze the markets overall reaction to reported insider sales. The results show that the initial market reaction is a highly significant 1-day abnormal return of -0.15%. The $\overline{CAR}$ is decreasing at a high rate suggesting that the market reaction to negative events has a stronger impact on future returns over time than purchases. The standard deviation is higher than for purchases and increases more rapidly, which may be caused by fewer observations on sales or higher risk in the stocks sold.

The highly significant results over the horizon and across models imply that insider sales can predict abnormal returns. We thereby reject the null hypothesis that the $\overline{CAR}$ is equal to zero on sales over time. All our models support this.

Result Discussion of Market Level Hypotheses

Our results seem to support the initial assumption that insiders are better informed about the overall future performance of their company. Our results are in line with the findings from Sjöholm and Skoog (2006) on the Swedish stock market, as well as Engevik and Helleren (2009), Omsted and Olsen (2014) and Holen (2008) on the Norwegian stock market.

As opposed to Jaffe (1974), our results does not display an initial overreaction followed by a reversion. Our results display a $\overline{CAR}$ increasing at a slightly decreasing rate over time, similar to the signs of stagnation found by Cohen, Malloy & Pomorski (2012). The evidence support that insider trades reveal information that has a permanent effect on the company's value and that the information is not efficiently handled by the market, suggesting that markets are not semi-strong efficient.

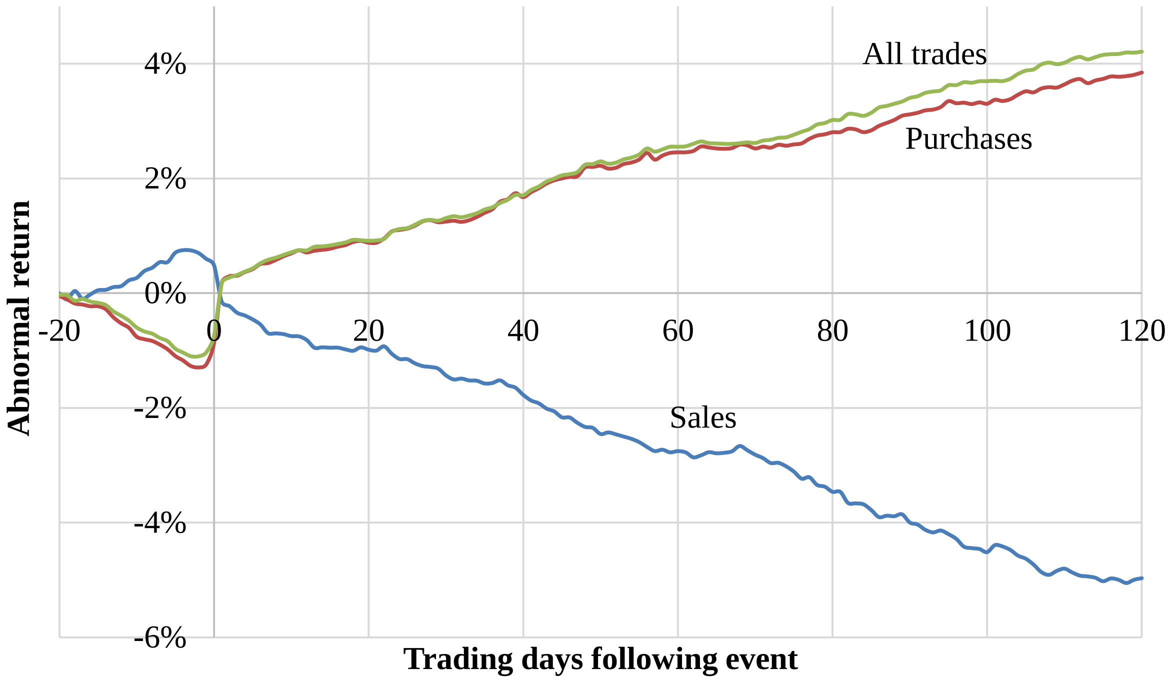

Figure 6 - Abnormal returns from insider trades

By including 20 days prior to the event, we can see that the event changes the trend in modeled returns pre-event. This strengthens the validity of our findings.

As we can observe from Table 10 and Figure 6, insider sales seems to give higher abnormal returns than purchases. We performed a t-test for differences in means[27], to test whether

[27] Welch's unequal variances t-test is used to perform tests for differences in mean

sales provide a stronger signal of abnormal returns than purchases. Our findings suggest this is the case for all horizons except 1D.

	Sales vs purchases
	P-value, $\lvert\mu_{sales}\rvert - \mu_{purchases} > 0$
1D	1.000
1M***	< 0.001
2M***	< 0.001
3M***	< 0.001
6M***	< 0.001

Table 11 - Results, sales vs purchases

Sjöholm and Skoog (2006), looking at purchases versus sales in the Swedish stock market between 1990 and 2004, get similar results. Still, these findings are contrary to most previous literature finding largest abnormal returns following insider purchases. We believe this finding can be a result of market differences between Swedish and other markets or that Swedish insiders, both when purchasing and selling, more often have a profit motive rather than a liquidity (or other) motive.

6.2 Firm Level

6.2.1 Market Capitalization

Hypothesis 2.1 – Insider trades in small cap companies provide a stronger signal of abnormal returns than mid and large cap companies

In the first hypothesis on a firm level, we apply our methods on three subsets of our data; small cap, mid cap and large cap stocks.

	Small cap			***Mid cap***			***Large cap***		
	Market MDL			**Market MDL**			**Market MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.37 %***	0.057 %	< 0.001	0.05 %	0.048 %	0.280	0.08 %**	0.035 %	0.017
1M	1.67 %***	0.254 %	< 0.001	0.34 %	0.213 %	0.113	0.72 %***	0.156 %	< 0.001
2M	2.99 %***	0.359 %	< 0.001	1.18 %***	0.302 %	< 0.001	0.87 %***	0.220 %	< 0.001
3M	3.96 %***	0.440 %	< 0.001	2.19 %***	0.370 %	< 0.001	1.40 %***	0.270 %	< 0.001
6M	5.99 %***	0.622 %	< 0.001	3.76 %***	0.522 %	< 0.001	2.75 %***	0.382 %	< 0.001
n	2275			2284			2068		

Table 12 - Results, small cap, mid cap and large cap. Market model

The results show that the initial market reaction is a highly significant 1-day abnormal return for small cap companies with a $\overline{CAR}$ of 0.37%. $\overline{CAR}$ is positive and significant for small and large cap over all horizons, but the results are not significant for mid cap for 1D and 1M. The return is highest for small cap, but these companies also have the highest volatility, measured by the standard deviation of abnormal returns.

In Figure 7, we can see how the abnormal returns are distributed among the different firm sizes for different horizons.

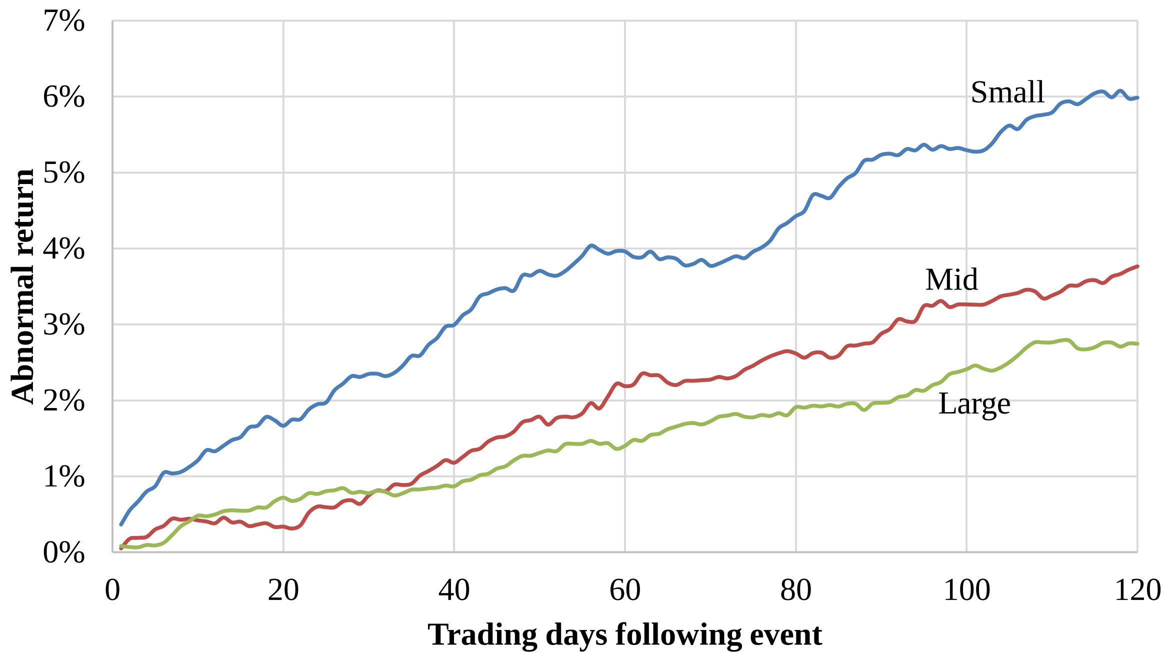

Figure 7 - Abnormal returns, firm size

To test whether small cap delivers higher results than mid and large cap firms, a t-test for differences in means was performed. The test results are shown in Table 13 below.

	Small vs Large	***Small vs Mid***
	P-value, $\mu_{small} - \mu_{large} > 0$	**P-value,** $\mu_{small} - \mu_{mid} > 0$
1D***	< 0.001	< 0.001
1M***	< 0.001	< 0.001
2M***	< 0.001	< 0.001
3M***	< 0.001	< 0.001
6M***	< 0.001	< 0.001

Table 13 - Results, small cap vs mid and large cap

The results are clear; small cap companies deliver a highly significant abnormal return over mid and large cap companies for all chosen horizons. We therefore reject the null hypothesis that small cap companies do not provide a stronger signal of abnormal returns than mid and large cap companies.

Our findings are in line with previous literature and our initial assumptions. There seems to be a negative correlation between abnormal returns and market capitalization, hence insider trades in smaller companies signal stronger abnormal returns following the trade. This may support what we hypothesized, that more information asymmetry exist in small cap companies, creating greater advantages for informed traders.

6.2.2 Growth vs Value Firms

Hypothesis 2.2 – Growth companies earn a significant higher abnormal return than value companies following the publication of insider trades

We have segregated the firms into growth companies and value companies[28].

	Growth companies			*Value companies*		
	Market MDL			**Market MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.27 %***	0.070 %	< 0.001	0.14 %***	0.049 %	0.005
1M	1.22 %***	0.315 %	< 0.001	0.57 %***	0.218 %	0.009
2M	1.88 %***	0.445 %	< 0.001	1.65 %***	0.309 %	< 0.001
3M	2.80 %***	0.545 %	< 0.001	2.70 %***	0.378 %	< 0.001
6M	4.37 %***	0.771 %	< 0.001	3.62 %***	0.535 %	< 0.001
n	1550			1556		

Table 14 - Results, growth vs value firms. Market model

The results show that the initial market reaction is a highly significant 1-day abnormal return for both growth and value companies. With a $\overline{CAR}$ of 0.27%, growth companies delivers almost double the 1-day return compared to value companies with a $\overline{CAR}$ of 0.14%. The difference in abnormal returns varies over the horizon, but growth companies seem to deliver slightly higher $\overline{CAR}$ for all horizons. Growth companies also have the highest standard deviation. In Figure 8, we can see how the abnormal returns are distributed among growth and value companies over the horizon.

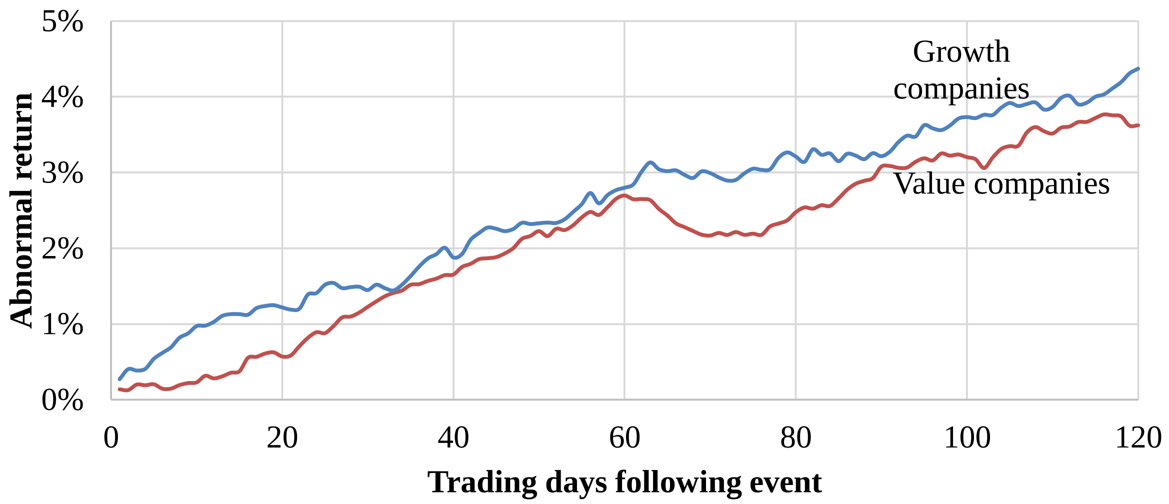

Figure 8 - Abnormal returns, growth vs value firms

[28] Growth companies are companies with high P/E ratios (4th quartile) and value companies are those with low P/E (1st quartile).

We performed a t-test for differences in means, to test if growth companies earn a statistically higher abnormal return than value companies (Table 15).

	Growth vs Value
	P-value, $\mu_{growth} - \mu_{value} > 0$
1D***	< 0.001
1M***	< 0.001
2M***	< 0.001
3M***	< 0.001
6M***	< 0.001

Table 15 - Results, growth vs value firms

Growth companies seem to deliver significant results over value companies for all tested horizons. We therefore reject the null hypothesis that growth companies does not earn a significant higher abnormal return than value companies following the publication of insider trades.

Our findings are in line with previous literature and our initial assumptions, suggesting that the market does not efficiently incorporate the present value of growth opportunities. Insider trades in growth companies signal stronger abnormal return following the trade than in value companies. This supports our assumptions that insiders possess greater knowledge of their company's growth opportunities and can take advantage of this information. In addition, the results show that the difference in abnormal returns between growth and value companies is initially high before converging after two months, indicating that the growth opportunities are momentarily incorporated. The results therefore seem to support our assumption that growth opportunities are *first* and *best* signaled by insiders.

6.2.3 Firm Leverage

Hypothesis 2.3 – Insider trades in companies with high financial leverage earn significant higher abnormal returns than companies with low financial leverage following the publication of insider trades

We have segregated the firms into highly leveraged firms and low leveraged firms[29].

	High leverage Market MDL			***Low leverage*** Market MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.03 %	0.048 %	0.523	0.21 %***	0.069 %	0.003
1M	0.45 %**	0.214 %	0.035	1.56 %***	0.307 %	< 0.001
2M	0.95 %***	0.303 %	0.002	2.60 %***	0.434 %	< 0.001
3M	2.11 %***	0.371 %	< 0.001	3.69 %***	0.531 %	< 0.001
6M	3.95 %***	0.524 %	< 0.001	5.26 %***	0.751 %	< 0.001
n	934			957		

Table 16 - Results, companies with high and low leverage. Market model

With the exception of 1-day $\overline{CAR}$ for highly leveraged firms that is not significant and the 1-month $\overline{CAR}$ that is significant at a 5% level, all $\overline{CAR}$ are highly significant for other horizons. What is a little surprising is that the $\overline{CAR}$s' standard deviation is higher for low leveraged firms than for highly leveraged firms.

In Figure 9, we can see how the abnormal returns are distributed over the horizon.

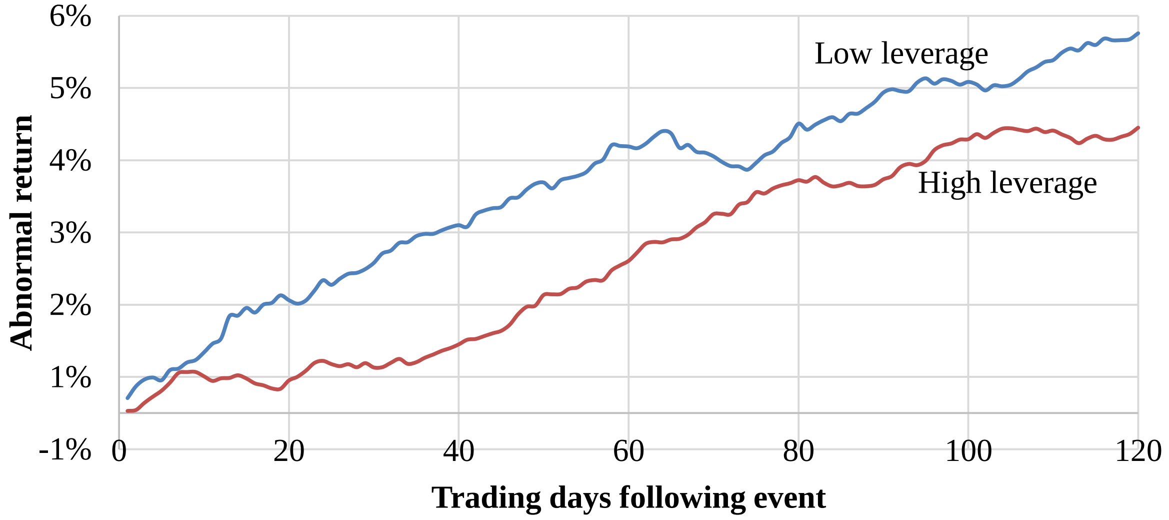

Figure 9 - Abnormal returns, high vs low leveraged firms

[29] Companies with D/E ratios in the 4th quartile will be classified as highly leveraged firms, and companies in the 1st quartile as firms with low leverage.

By looking at Figure 9, we can immediately see that we do not reject the null. We observe that insider trades in firms with low leverage earn higher abnormal returns than companies with high financial leverage following the trade, for all horizons. Insider trades in companies with high financial leverage **does not** earn significant higher abnormal returns than companies with low financial leverage following the publication of insider trades.

We hypothesized that high leverage could create potential opportunities and incentives for moral hazard or adverse selection and magnify the outcome of a trade. In contrast to our expectations, low leveraged firms deliver a larger abnormal return than highly leveraged firms following the publication of insider trades. The results suggests that the information value and signaling powers of insiders in highly leveraged firms are relatively weaker than in low leveraged firms. Even though our initial assumptions were not validated, we find the results interesting, as they indicate that capital structure affect the information value of insider trades.

6.2.4 Firm Industry

Hypothesis 2.4 – There is a difference in abnormal returns across industries

	Basic Materials		*Consumer Goods*		*Consumer Services*		*Financials*		*Health Care*	
	Market MDL		**Market MDL**		**Market MDL**		**Market MDL**		**Market MDL**	
	CAR-bar	**σ**	**CAR-bar**	**σ**	**CAR-bar**	**σ**	**CAR-bar**	**σ**	**CAR-bar**	**σ**
1D	0.28 %*	0.166 %	0.12 %	0.092 %	0.00 %	0.079 %	0.09 %**	0.037 %	0.37 %***	0.137 %
1M	-0.35 %	0.741 %	0.41 %	0.411 %	0.80 %**	0.354 %	0.44 %***	0.165 %	3.53 %***	0.615 %
2M	0.06 %	1.048 %	1.34 %**	0.581 %	1.20 %**	0.500 %	0.67 %***	0.234 %	4.44 %***	0.870 %
3M	-0.30 %	1.284 %	3.07 %***	0.712 %	1.79 %***	0.613 %	1.21 %***	0.286 %	7.05 %***	1.065 %
6M	1.46 %	1.815 %	2.68 %***	1.007 %	5.39 %***	0.867 %	2.98 %***	0.405 %	11.06 %***	1.507 %
n	352		651		789		1400		556	

	Industrials		*Oil & Gas*		*Technology*		*Telecommunications*		*Utilities*	
	Market MDL		**Market MDL**		**Market MDL**		**Market MDL**		**Market MDL**	
	CAR-bar	**σ**	**CAR-bar**	**σ**	**CAR-bar**	**σ**	**CAR-bar**	**σ**	**CAR-bar**	**σ**
1D	0.24 %***	0.052 %	0.96 %*	0.553 %	0.19 %**	0.086 %	-0.02 %	0.107 %	-0.05 %	0.460 %
1M	0.58 %***	0.234 %	3.23 %	2.472 %	1.69 %***	0.387 %	1.48 %***	0.481 %	0.08 %	2.061 %
2M	1.50 %***	0.330 %	7.90 %**	3.496 %	3.64 %***	0.547 %	2.13 %***	0.680 %	1.07 %	2.915 %
3M	2.22 %***	0.405 %	15.39 %***	4.282 %	4.36 %***	0.670 %	1.87 %**	0.832 %	-2.06 %	3.570 %
6M	2.89 %***	0.573 %	31.99 %***	6.055 %	6.39 %***	0.948 %	1.45 %	1.177 %	4.17 %	5.048 %
n	1922		28		653		257		19	

Table 17 - Results, firm industry. Market model

As expected, the distribution of $\overline{CAR}$s among industries vary a lot. Oil & Gas, although few observations, show an extremely large and highly significant abnormal return of 31.99% on the 6-month horizon. Telecommunications, together with Basic Materials, Financials and Industrials, seems to deliver low abnormal return compared to other industries. It is interesting to see that Health Care and Technology delivers significant and highly significant and large $\overline{CAR}$s over all the tested horizons.

In Figure 10, we can see how the abnormal returns are distributed among some of the industries. Oil & Gas and Telecommunications were removed from the figure due to few observations and various degree of significance in the different models and for different horizons. Utilities had very few observations, and were together with basic materials not significant for any horizons. We were then left with Health Care, Technology, Consumer Service, Industrials and Consumer Goods.

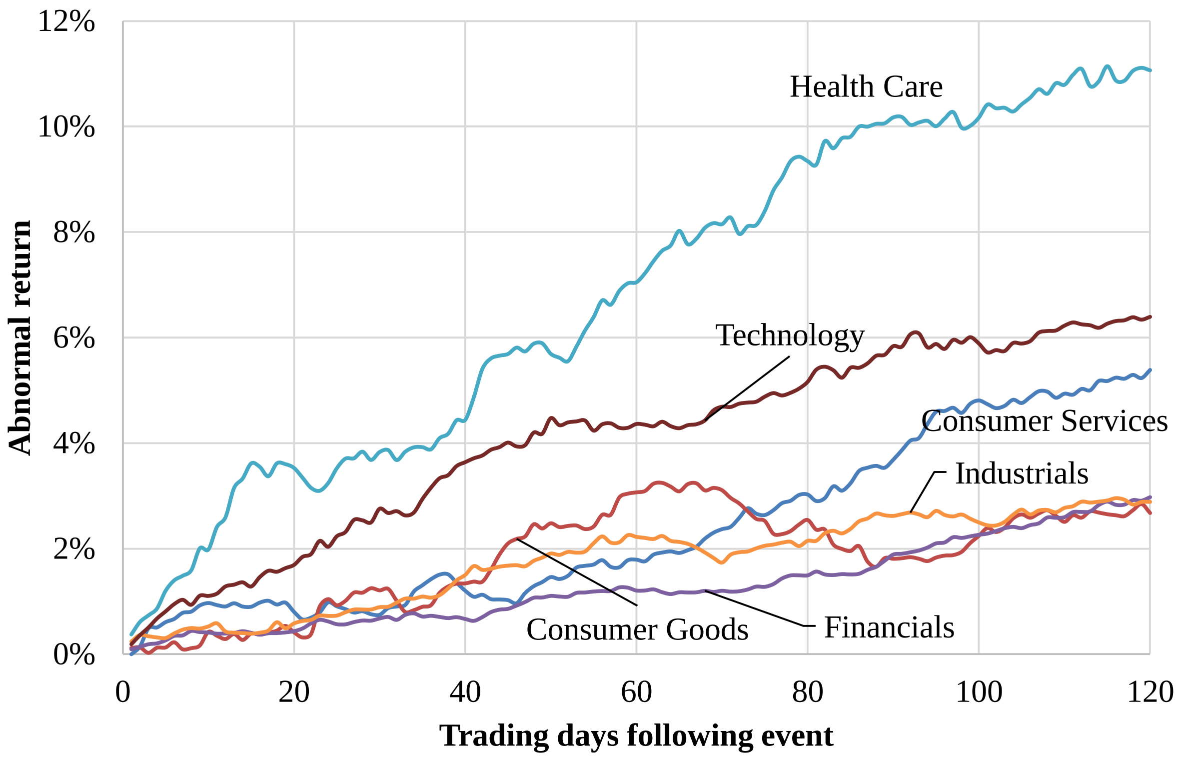

Figure 10 - Abnormal returns, firm industry

We tested all industries against each other[30]. The most important findings are that the health care industry's $\overline{CAR}$ are significantly higher than all other industries on a 1% level, with the exception of oil & gas. Following health care and oil & gas, the technology industry shows $\overline{CAR}$ higher than the other industries for all horizons at a 1% significance level, with an exception of 1-day returns against some industries. Our data indicates that there is a difference in abnormal returns across industries and we reject the null that there is no difference between industries when it comes to abnormal returns following the publication of insider trades.

Similarly to Seyhun (1998) we find that by aggregating insider trading in different industries, one can strengthen the signal of the abnormal return. We find it corroborative that industries characterized by highly sensitive information, such as Health Care and Technology, displays the strongest abnormal returns. This supports our assumptions that information from complex industries may be difficult for outside investors to fully comprehend, thereby causing informational asymmetries.

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[30] Test results for all industries can be found in Appendix E – 2.4 Firm Industry. You will also find each single industry tested against each other using Welch's t-test.

6.2.5 Firm Reporting

Hypothesis 2.5 – Trades adjacent to quarterly reports provide a weaker signal of abnormal returns than trades not adjacent to quarterly reports

We have segregated the trades into trades adjacent to quarterly reports and trades not adjacent to quarterly reports growth[31].

	Adjacent to quarterly reports			*Not adjacent to quarterly reports*		
	Market MDL			**Market MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.12 %***	0.040 %	0.003	0.21 %***	0.038 %	< 0.001
1M	0.85 %***	0.178 %	< 0.001	0.96 %***	0.171 %	< 0.001
2M	1.41 %***	0.252 %	< 0.001	1.93 %***	0.242 %	< 0.001
3M	2.08 %***	0.308 %	< 0.001	2.91 %***	0.297 %	< 0.001
6M	3.84 %***	0.436 %	< 0.001	4.49 %***	0.420 %	< 0.001
n	2881			2284		

Table 18 - Results, firm reporting. Market model

First of all, we notice that both data subsets $\overline{CAR}$s' are highly significant for all tested horizons. From Table 18, we can also see that trades not adjacent to quarterly reports seem to deliver higher $\overline{CAR}$s' following the trade than those adjacent to quarterly report. The distribution is shown in Figure 11.

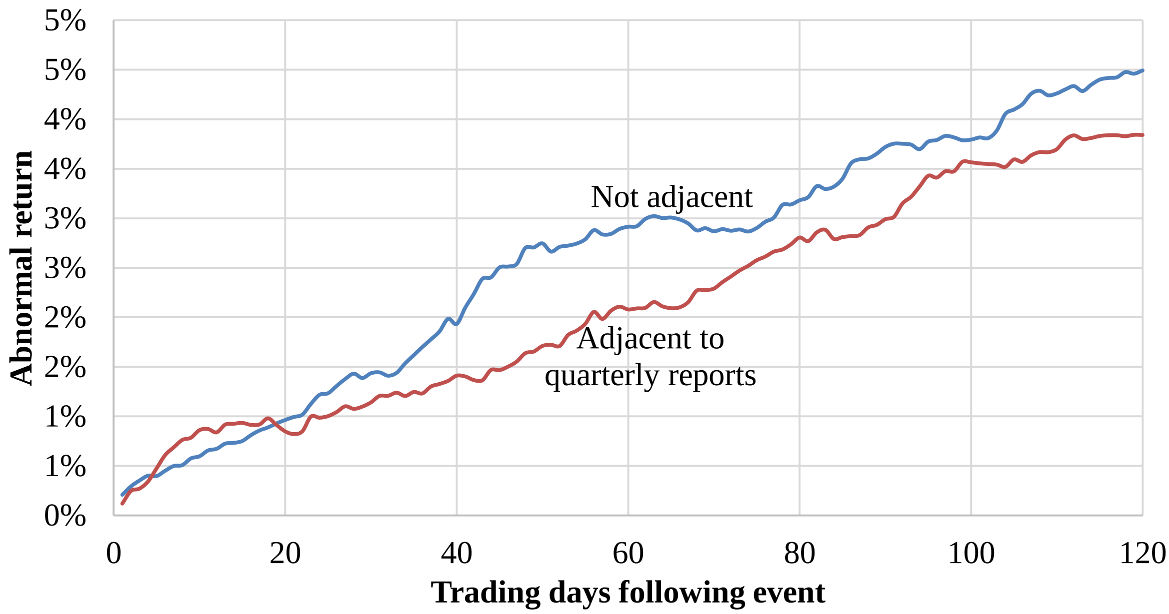

Figure 11 - Abnormal returns, firm reporting

[31] Trades adjacent to quarterly reports are all trades performed in the months following the quarterly reports. Trades not adjacent to quarterly reports are the other eight months.

The figure indicates what we expect, that trades adjacent to quarterly reports provide lower abnormal returns than trades not adjacent to quarterly reports – with some exceptions in the first 20 days following the event. To check the significance, we performed t-tests for differences in means (Table 19).

	Adjacent vs not adjacent to quarterly reports
	P-value, $\mu_{adj} - \mu_{not\ adj} < 0$
1D***	< 0.001
1M***	< 0.001
2M***	< 0.001
3M***	< 0.001
6M***	< 0.001

Table 19 - Results, firm reporting

For all tested horizons, trades adjacent to quarterly reports delivers lower abnormal returns on a 1% significance level. We therefore reject the null hypothesis that trades adjacent to quarterly reports provide a **stronger** signal of abnormal returns than trades not adjacent to quarterly reports

These results are in line with our initial assumptions; the abnormal returns after insider trades are in general weaker in months adjacent to quarterly reports. As we argued in Chapter 3, we believe that quarterly reporting reveals information that contributes to a more efficient market. The consequence is that any superior information insiders may have had diminishes, narrowing the informational gap between insiders and outsiders.

6.2.6 Momentum

Hypothesis 2.6 – Insider trades in companies with momentum earn a significant higher abnormal return following the trade than insider trades in companies without momentum

We have segregated the trades into trades with momentum and trades without momentum[32].

	Momentum			***No momentum***		
	Market MDL			**Market MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.23 %***	0.045 %	< 0.001	0.11 %***	0.033 %	0.001
1M	1.16 %***	0.201 %	< 0.001	0.67 %***	0.146 %	< 0.001
2M	2.50 %***	0.284 %	< 0.001	0.91 %***	0.206 %	< 0.001
3M	3.64 %***	0.348 %	< 0.001	1.46 %***	0.252 %	< 0.001
6M	6.66 %***	0.492 %	< 0.001	1.76 %***	0.356 %	< 0.001
n	3313			3314		

Table 20 - Results, momentum. Market model

As for the previous hypothesis, we notice that both data subsets $\overline{CAR}$ are highly significant for all tested horizons. From the table, we can also see that insider trades in firms with momentum seem to deliver higher $\overline{CAR}$ following the trade than those in firms with no momentum.

In Figure 12, we can see how the abnormal returns are distributed.

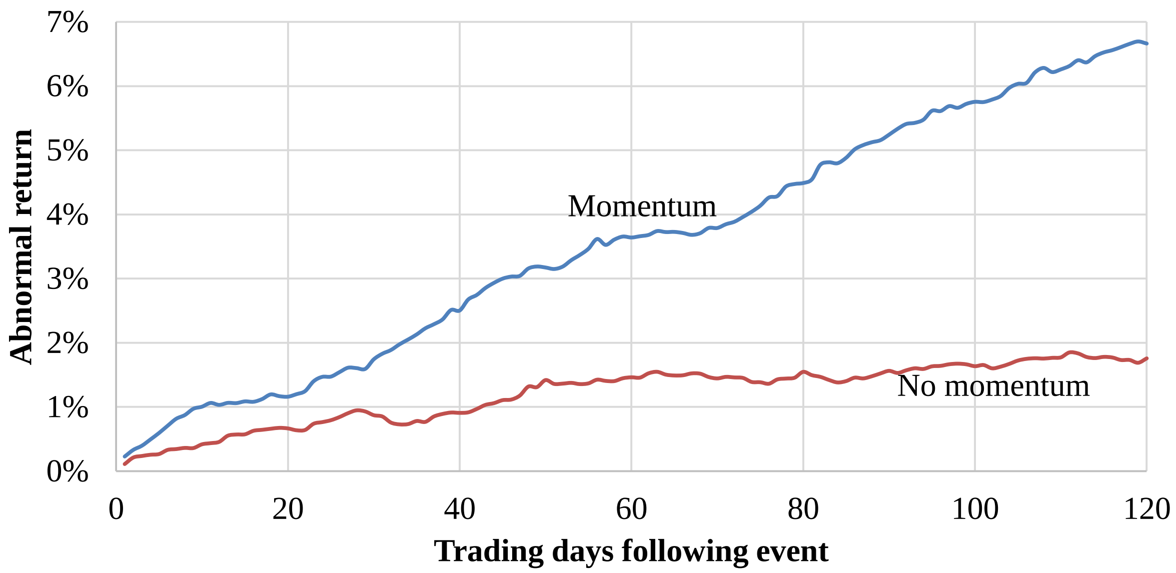

Figure 12 - Abnormal returns, trade momentum

[32] We ranked all the stocks by their return 120 trading days prior to the trade, and classified insider trades with momentum as insider trades done in the 4th quartile of returns (positive momentum) **and** insider trades in the 1st quartile (negative momentum). Trades in the 2nd and 3rd quartile were classified as trades without momentum.

The figure indicates what we expected. To check the significance, we performed t-tests for differences in means (Table 21).

	Momentum vs no momentum
	P-value, $\mu_{mom} - \mu_{no\_mom} > 0$
1D***	< 0.001
1M***	< 0.001
2M***	< 0.001
3M***	< 0.001
6M***	< 0.001

Table 21 - Results, momentum

For all tested horizons, insider trades with momentum earn significantly higher returns than trades without moment on a 1% level. We therefore reject the null hypothesis that trades adjacent to quarterly reports provide a **stronger** signal of abnormal returns than trades not adjacent to quarterly reports

Our results are consistent with previous literature and support our initial assumptions. There seems to occur a synergy effect when an insider trades in a company that has experienced momentum the preceding six months. Our results suggest that if an insider trades in a company with momentum, the following abnormal returns are stronger than for a company without momentum.

6.3 Individual level

6.3.1 Insider Position

Hypothesis 3.1 – There is a difference in abnormal returns across insiders with different firm positions

	Alternate and/or subsidiary bm			*Board member parent firm*			*Large shareholder*		
	Market MDL			**Market MDL**			**Market MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.03 %	0.237 %	0.903	0.20 %***	0.056 %	< 0.001	0.11 %	0.084 %	0.175
1M	2.89 %***	1.058 %	0.007	0.94 %***	0.250 %	< 0.001	-0.98 %***	0.375 %	0.009
2M	5.29 %***	1.497 %	< 0.001	1.75 %***	0.354 %	< 0.001	-0.74 %	0.531 %	0.164
3M	6.47 %***	1.833 %	< 0.001	2.27 %***	0.432 %	< 0.001	-0.10 %	0.651 %	0.873
6M	9.63 %***	2.592 %	< 0.001	4.69 %***	0.612 %	< 0.001	-3.84 %***	0.920 %	< 0.001
n	148			2008			798		
	Managing Director			*Other executive*			*Other position*		
	Market MDL			**Market MDL**			**Market MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.39 %***	0.090 %	< 0.001	0.00 %	0.084 %	0.994	0.13 %***	0.040 %	< 0.001
1M	1.89 %***	0.401 %	< 0.001	0.55 %	0.374 %	0.146	1.16 %***	0.180 %	< 0.001
2M	4.07 %***	0.567 %	< 0.001	0.44 %	0.530 %	0.405	1.85 %***	0.255 %	< 0.001
3M	6.27 %***	0.695 %	< 0.001	0.88 %	0.649 %	0.177	2.79 %***	0.312 %	< 0.001
6M	10.86 %***	0.982 %	< 0.001	2.35 %**	0.918 %	0.011	4.76 %***	0.440 %	< 0.001
n	662			475			2504		

Table 22 - Results, insider position. Market model

As expected, the distribution of $\overline{CAR}$s' following trades made by insiders in different positions vary a lot. In Figure 13, we can see how the abnormal returns are distributed among the different insider positions.

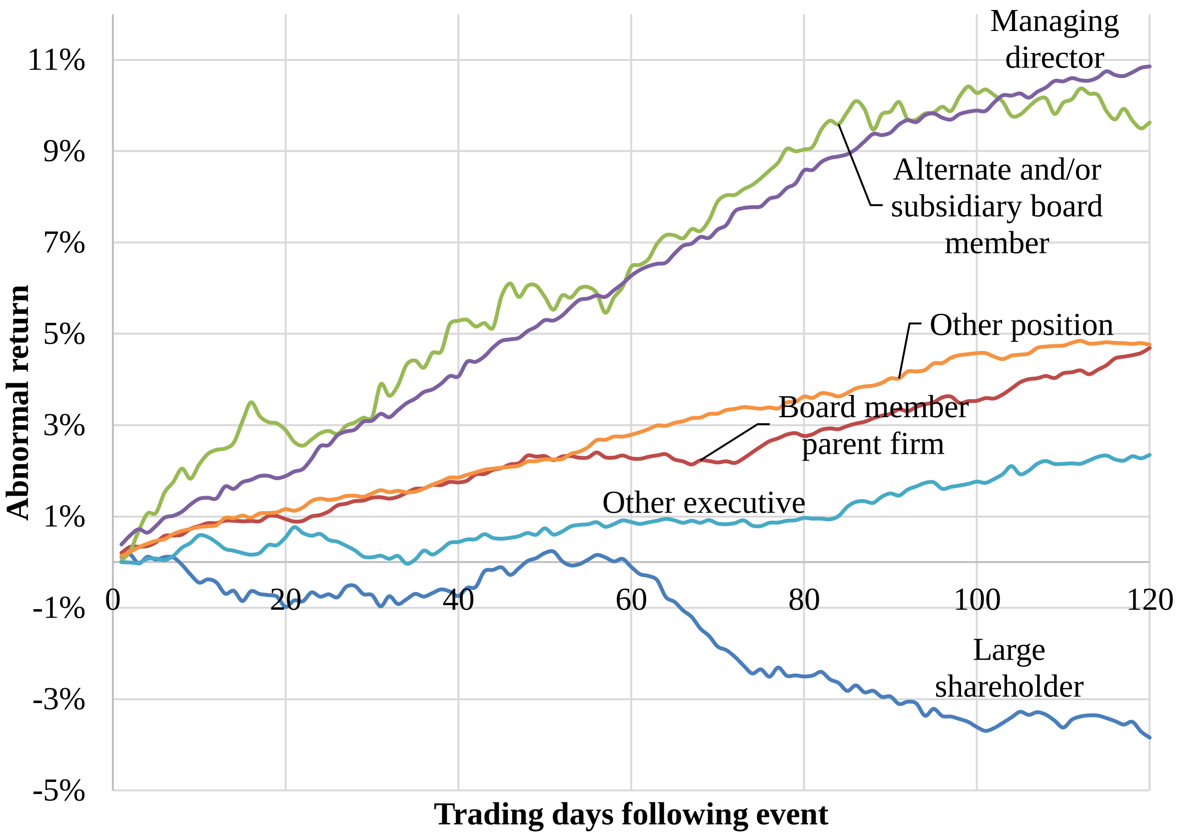

Figure 13 - Abnormal returns, insider position

We tested all insider positions against each other[33]. The highest abnormal returns are gained by following insider trades made by Managing Directors and Alternate and/or subsidiary board members.

The most important finding is that Managing Directors signal higher abnormal returns than all other insider position groups on a 1% level, with the exception of Alternate and/or subsidiary board members (1M, 2M and 3M). Alternate and/or subsidiary board members has the smallest number of observations, and the multifactor return model (please consult Appendix E – Insider Position) shows less significant results for 1M and 2M and no significant results for the other tested horizons. We should therefore be careful when interpreting the results from this insider group.

Board member parent firm and Other position signals higher abnormal returns than Other executive do. Only Large shareholder seem to signal negative abnormal returns over the

[33] Test results for all insider positions can be found in Appendix E – 3.1 Insider Position. You will also find each group of insiders tested against each other using Welch's t-test.

horizon, although the level of significance vary over the horizon and across the different return models (Please consult Appendix E – 3.1 Insider Position).

Our data indicates that there is a difference in abnormal returns following insider trades performed by insiders in different positions within the firm. We therefore reject the null that there is no difference in abnormal returns across insiders with different firm positions. Contrary to previous literature, we do not succeed to reveal a distinction between low and high profile insiders. For example, Managing Director clearly outperforms Board member parent firm, even though both surely must be considered high profile. The results do however show obvious differences between our designated insider positions. Managing Director presents the strongest abnormal returns. This can indicate that insiders with a higher assumed overall knowledge of their firm exhibit the largest informational value. On the other hand, Large shareholder seems to underperform. We believe a possible explanation could be that trades made by large shareholders are more often motivated by diversification, liquidity and tax motives.

6.3.2 Trade Volume - Absolute

Hypothesis 3.2 – Small *absolute volume* insider trades provide a stronger signal of abnormal returns than large *absolute volume* insider trades

We have segregated the trades into small absolute volume and large absolute volume[34].

	Small absolute volume			***Large absolute volume***		
	Market MDL			**Market MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.17 %***	0.064 %	0.008	0.11 %**	0.052 %	0.041
1M	1.30 %***	0.285 %	< 0.001	0.28 %	0.231 %	0.227
2M	2.51 %***	0.402 %	< 0.001	1.20 %***	0.327 %	< 0.001
3M	3.44 %***	0.494 %	< 0.001	2.12 %***	0.400 %	< 0.001
6M	5.51 %***	0.698 %	< 0.001	3.76 %***	0.567 %	< 0.001
n	1622			1646		

Table 23 - Results, absolute volume. Market model

The results show that the initial market reaction is a highly significant 1-day abnormal return of 0.17% for small absolute volume trades and a significant 1-day abnormal return of 0.11% for large absolute trade volumes. The difference in $\overline{CAR}$s' varies over the horizon, but small absolute trade volumes seems to deliver higher returns following an insider trade overall, with a highly significant 6-month abnormal return of 5.51% versus 3.76% for large absolute volume trades. In Figure 14, we can see how the abnormal returns are distributed.

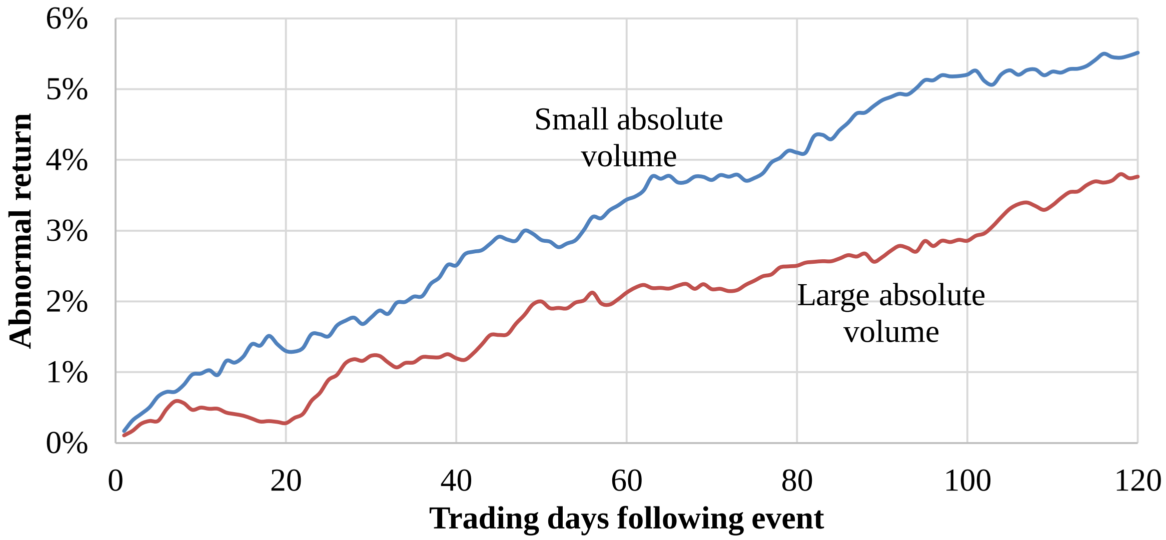

Figure 14 - Abnormal returns, absolute volume

[34] We have classified small absolute volume insider trades as trades with an absolute volume in the 1st quartile of all traded volumes. Large absolute volume insider trades are those in the 4th quartile.

The figure indicates what we expect, that small absolute volume insider trades provide a stronger signal of abnormal returns than large absolute volume insider trades. To check the significance, we performed t-tests for differences in means (Table 24).

	Small absolute volume vs large absolute volume
	P-value, $\mu_{small\_abs} - \mu_{large\_abs} > 0$
1D***	< 0.001
1M***	< 0.001
2M***	< 0.001
3M***	< 0.001
6M***	< 0.001

Table 24 - Results, absolute volume

For all tested horizons, small absolute volume insider trades provide a stronger signal of abnormal returns than large absolute volume insider trades on a 1% significance level. We therefore reject the null.

The results are in line with our reasoning. Contrary to Seyhun (1986) and Omsted and Olsen (2014), we find that small absolute volume trades display the strongest abnormal returns. As we argued in Chapter 3, we believe that small absolute volume trades are more often motivated by profit than large absolute volume trades are, which may help explain our results.

6.3.3 Trade Volume - Relative

Hypothesis 3.3 – Large *relative volume* insider trades provide a stronger signal of abnormal returns than small *relative volume* insider trades

We have segregated the trades into small relative volume and large relative volume[35].

	Large relative volume			***Small relative volume***		
	Market MDL			**Market MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.24 %***	0.058 %	< 0.001	0.26 %***	0.057 %	< 0.001
1M	1.50 %***	0.257 %	< 0.001	0.33 %	0.257 %	0.193
2M	2.60 %***	0.363 %	< 0.001	1.04 %***	0.363 %	0.004
3M	3.46 %***	0.446 %	< 0.001	1.56 %***	0.445 %	< 0.001
6M	5.65 %***	0.630 %	< 0.001	2.07 %***	0.629 %	0.001
n	1646			1648		

Table 25 - Results, relative volume. Market model

The results show that the initial market reaction is a highly significant 1-day abnormal return of 0.24% for large relative volume trades and 0.26% for small relative trade volumes. With the exception of the 1-day return, large relative volume trades seem to signal higher abnormal returns following an insider trade than small relative volume trades. The distribution of the abnormal returns is found in Figure 15 below.

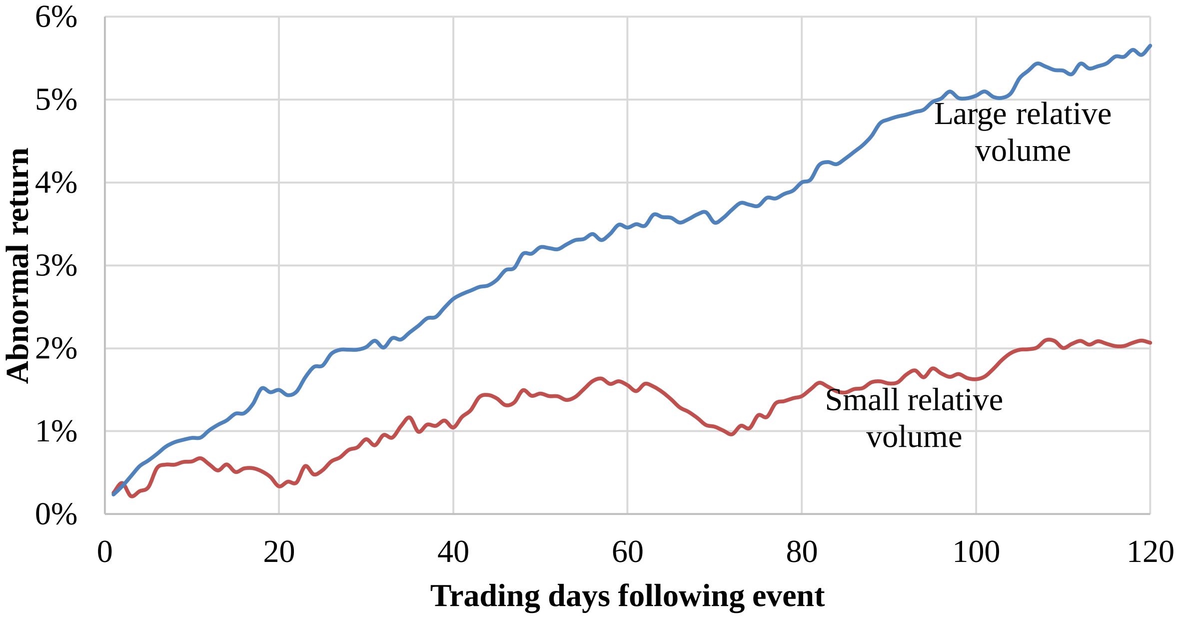

Figure 15 - Abnormal returns, relative volume

35 Small relative volume insider trades are trades with a relative volume in the 1st quartile of all traded relative volumes. Large relative volume insider trades are those in the 4th quartile

The figure indicates what we expect; large relative volume insider trades provide a stronger signal of abnormal returns than small relative volume insider trades. To check the significance, we performed t-tests for differences in means (Table 26).

	Large relative volume vs small relative volume
	P-value, $\boldsymbol{\mu_{large\_rel} - \mu_{small\_rel} > 0}$
1D	1.000
1M***	< 0.001
2M***	< 0.001
3M***	< 0.001
6M***	< 0.001

Table 26 - Results, relative volume

For all tested horizons, with the exception of 1-day, large relative volume insider trades provide a stronger signal of abnormal returns than small relative volume insider trades on a 1% significance level. We therefore reject the null.

The results support our initial reasoning. Large relative volume trades outperform small relative volume trades. We believe the relative volume signals the confidence the insider has to his information and firm specific knowledge. Our results support this logic, displaying higher abnormal return following the trade for higher relative trade volume.

6.4 Research Critique

Statistical difficulties with measurement of abnormal returns may be the result of survivorship bias, bias in the estimation of normal returns, confounding events, clustering of events or thin trading. Most of these biases increase with the length of the event study, and short-term event studies can be said to be more reliable than longer-term event studies.

Survivorship Bias

Missing return data in the 120 trading days prior to the event taking place (estimation window) or in the 120 trading days following the event taking place (event window) leads to the exclusion of some firms. This can lead to survivorship bias, inflating the estimates of abnormal returns as a few firms with extremely low return (default) are excluded. The inflated estimates will be more frequent in data subsets with higher probabilities of default (e.g. small cap firms and firms with very high leverage).

Estimation of Normal Returns

From 2010 until 2014, the Swedish stock market was a bull market. The exception was during the multi-year European debt crisis peaking in 2011, caused by the selective default on Greek and other Eurozone member states governmental debt. The NASDAQ OMX Stockholm All-Share Index fell 28% from its top the 3rd of January 2011 to the bottom the 4th of October 2011. One could see this drop as an “unusual” return, which would affect the estimation of normal returns in the period and inflate abnormal returns in the following period. On the other hand, abnormal returns with an event window during the market drop will be understated when the normal return is estimated from the bull market before the drop.

Confounding Events

Events other than the publication of insider trades either in the estimation window or in the event window can have huge impact on the $\overline{CAR}$s. In the estimation window (the 120 days prior to the event taking place) firm-specific news with a huge share price impact would greatly influence our estimation of the firms normal return, leading to either increasing or decreasing our estimate of abnormal returns following the event. In the event window (the 120 trading days following the event), there is a high probability of other firm-specific events occurring. Both internal events, such as the firm signing a huge contract, and external events, such as advantageous amendments of laws and regulation, can have a significant share price impact. This will affect the estimation of abnormal returns.

We argue that due to a large amount of observations and that the mentioned events can affect either the estimation of normal returns (estimation window) or the estimation of abnormal returns (event window) both positively and negatively, the bias will most likely be small on average.

Event Clustering

We have not dealt with event clustering. This causes event windows of included securities to overlap, potentially causing covariance in abnormal returns across securities. For example can a macroeconomic event affecting the overall market, such as the Standard & Poor's Ratings Service downgrade of Greek short-term sovereign credit ratings to “SD” (selective default) the 27th of February 2011, influence the abnormal returns of all securities that have the date of the macroeconomic event in their event window. This will be in violation of the independence assumption for abnormal returns. The problem increases with the length of the event window.

As long as the events are randomly distributed in our research period, the average bias in estimated $\overline{CAR}$s will be neglectable. A bigger issue relates to the fact that event clustering lead to less variability in abnormal returns across firms, resulting in a downward bias of the standard deviation estimate. This will affect test statistics and we could falsely reject the null hypothesis (Type I error). On the positive side, our securities are rather heterogeneous and the events are distributed fairly well over the research period making this issue less serious. On the negative side, our data subsets are often more homogenous, potentially leading to falsely rejecting the null hypotheses when testing on a firm and individual level.

Using the multifactor model to estimate normal returns will reduce issues related to event clustering. Kothari and Warner (2006) state that adjusting for clustering is critical first when the event window span over a year.

Liquidity

Some events are in stocks with little liquidity. Thin trading can bias the calculation of the beta in the market model and thus the normal and abnormal returns. As referred to by Mackinlay (1997, p. 36), Scholes and Williams (1977) found that the beta of securities with little trading were underestimated, meaning that normal returns in the market model will be underestimated for such stocks. This will inflate abnormal returns. As we look at securities noted on the main index for the Swedish Stock Market, we believe thin trading does not pose a significant threat to our results.

7. Optimal Insider Portfolio

The purpose of the hypotheses testing was to provide a statistical foundation for a real life trading strategy based on the signal sent by the publication of insider trades. To support that purpose we will make use of our findings on the market, firm and individual level to create three “optimal” insider portfolios by including securities with a high likelihood of abnormal returns following the insider trade.

In this chapter, we will present our testing methodology, test results and assessment of our insider portfolios. At the end of the chapter, we will look at drawbacks of our approach.

7.1 Method

First, we define the criteria for selecting the securities to be included in our portfolios. Then we describe the portfolios composition parameters and the methodology applied to test them.

7.1.1 Selection Criteria

We have chosen three portfolios for further testing. As a certain amount of valid insider signals to make portfolios with a reasonable amount of stocks is needed, we choose only two criteria per portfolio.

Portfolio #1	**Portfolio #2**	**Portfolio #3**
Small and mid cap companies	Small and mid cap companies	All companies
Large relative volume trades	Small absolute volume trades	Managing Director

Table 27 - Optimal Insider Portfolios

In portfolio #1, a valid insider signal is when an insider trade is done with a large relative trade volume in a small or mid cap company.

In portfolio #2, a valid insider signal is when an insider trade is done with a small absolute trade volume in a small or mid cap company.

In portfolio #3, a valid insider signal is when a trade is done by a Managing Director.

The portfolios are long-only. Insider sales are not valid signals because we, as outsiders, would have to short-sell the securities. As we would need someone to lend us their shares for short-selling, it is not always possible. The more difficult it is to find someone willing to lend us their shares for short-selling, the more expensive it is. For practical reasons, we therefore exclude these signals.

7.1.2 Portfolio Composition

Using our selection criteria we are left with a limited investment universe, which statistically has proven to amplify abnormal returns from reported insider trades. To start composing portfolios we need to define certain parameters.

Inclusion Date

Stocks are included the day after the valid insider signal at the security's opening price.

Holding Period (HP)

As event-studies are less robust for longer time-periods[36], we have chosen to test our three optimal insider portfolios for holding periods of both 1-month and 2-months, giving us a total of 6 portfolios. After a valid signal for the given portfolio, the security will be bought and held for 1-month or 2-months.

Subsequent Trades

If subsequent insider trades occur in a security already included in our portfolio, this is considered as a new signal for abnormal returns. Instead of purchasing the security more than once, the holding period of that security will be extended accordingly. It does not need to be the same insider trading for this to be true.

Weighting

Considering the weighting of the portfolios, two methods are commonly used.

Equal weight is the simplest method of determining the weight of each security in a portfolio. This method applies the same weight to all securities. For example, if you have four stocks in your portfolio, each stock has a weight of 25 % (1/4). The advantage of an equally weighted portfolio is that all stocks are allowed to perform and contribute on the same level. This is especially useful for portfolios containing companies with different market capitalization; small and large capitalized stocks are then weighted equally. The drawback is that the disproportionate increase in small cap stocks may increase the overall risk of the portfolio. The weight, $w_{i,t}$, is given by:

$$w_{i,t}^{equal} = \frac{1}{N} \quad \forall \quad i \subseteq N \qquad (9.1)$$

The alternative is *cap-weighting*. The objective of a cap-weighted portfolio is to assign the weighting based on the market capitalization of the company. The larger market capitalization as a percentage of the total market capitalization of the portfolio (or market),

[36] See 6.4 – Research Critique

the larger the share in the portfolio. The advantage of such a weighing method is that the portfolio weights become representative for the actual relation between the stocks themselves and the relation to the benchmark, both in risk and in return. The drawback of cap-weighted portfolios is usually connected to choosing a frequency of rebalancing. The weight, w_i, is given by:

$$w_{i,t}^{cap} = \frac{C_i}{\sum_{i=1}^{N} C_i} \quad \forall \quad i \subseteq N \tag{9.2}$$

Where C_i is the market capitalization of the stock.

We have chosen to weight the portfolios by using equal weights. As we find the strongest signal of abnormal returns in small cap companies, we believe our portfolios would benefit from equal weights as the weighting increases the relative proportion of small cap companies to mid and large cap companies.

Rebalancing

Our portfolios are rebalanced whenever there are new valid insider signals. At each trading day, the stocks with insider signals are included with equal weights. If there is no valid signal a given day, the weights of the stocks in the portfolio will fluctuate over time with the return of the stock. At the next rebalancing, any excess returns will be reinvested, keeping the total weights at 100% at all times. No capital gains or losses will be realized before the holding period expire. Daily rebalancing creates a high turnover ratio, and thus high transaction costs. The allowance of weights to fluctuate in periods with no valid signals, are an attempt to reduce the frequency of rebalancing and thereby transaction costs.

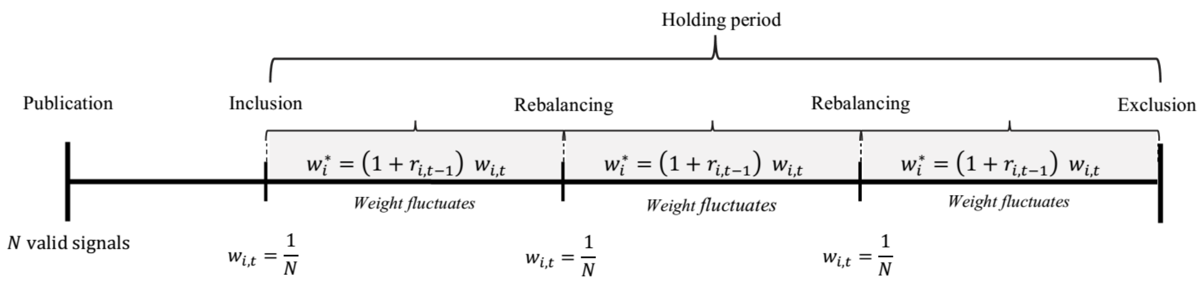

Figure 16 - Illustration of portfolio construction

At each publication of a valid signal, the stock will be included with equal weight the following day. The stocks respective weight will fluctuate with the return, unless a new signal arises which will require rebalancing. The holding period for each stock will be 1 or 2 months, as defined by the portfolio. Without any prolonging signals, the stock will be excluded at the end of it´s holding period.

7.1.3 Portfolio Performance

To meaningfully evaluate the risk-adjusted performance of the portfolios we need to define how to measure risk and return.

Risk

Risk can be thought of as the uncertainty of the expected return. It is measured by standard deviation (volatility) or beta. For a portfolio, we generally divide the total risk into two sub-categories: systematic risk and unsystematic risk.

Systematic risk (Also known as market- or non diversifiable risk) is the risk of events affecting the overall market, not just a particular investment or industry. Events affecting the overall market are caused by changes in macroeconomic factors such as economic output, unemployment, inflation, savings and investments, or by situations affecting the macroeconomic environment such as recessions or wars. It is possible to mitigate some systematic risk by hedging against systematic risk factors; however, this comes at a price (premium).

Unsystematic risk (Also known as firm-specific-, diversifiable- or unique risk) is the risk of events affecting a particular stock (investment) or industry. Examples of events affecting a particular stock or industry are labor strikes, mismanagement, plummeting sales, collapse in output prices or increase in input prices, natural disasters, new competitors or regulatory changes. By diversifying, we can reduce our exposure to this type of risk. A well-diversified portfolio consists of different types of securities from different industries, and unsystematic risk factors will offset each other. As shown by Statman (1987), portfolio (unsystematic) risk does fall by selecting stocks at random as a function of stocks in the portfolio, but the ability of diversification to reduce risk is limited by systematic sources of risk.

Beta is based on the statistical property of covariance and measures the systematic risk. It is used as the risk measure when we are holding *not only* the portfolio, ie. the portfolio is one among many assets. A beta of 1 indicates that the returns of a security will move with the returns of the market, a beta > 1 indicates that the returns will move more than the returns of the market, a beta < 1 indicates that the returns will move less than the returns of the market while a beta < 0 indicates that a security moves in the opposite way of the market.

Standard deviation (volatility) is a statistical measure of dispersion around a central tendency and is used as the risk measure when holding *only* the portfolio, i.e. the portfolio is our only asset. Standard deviation is assessing performance by total risk and does not categorize by systematic- or unsystematic risk. We use the standard deviation to measure risk[37], calculated as:

$$\sigma_{p,annualized} = \sigma_{p,daily} \times \sqrt{250} \tag{10.1}$$

Return

A single securities return is calculated daily in logarithmic terms. To calculate the daily portfolio return we aggregate the weighted daily returns of each security.

$$r_{p,t} = \sum_{i=1}^{N} r_{i,t} w_{i,t} \tag{10.2}$$

The total return for the portfolio will then be the aggregated daily returns.

$$R_p = \sum_{t=1}^{T} r_{p,t} \tag{10.3}$$

For performance measurement, we use the arithmetic return.

$$R_{A,p} = e^{R_p} - 1 \tag{10.4}$$

[37] There are other sources of risk not accounted for using the measures mentioned above, such as shortfall risk or drawdown. Behavioral finance addresses these types of risk.

Performance Measurement

We will assess our optimal insider portfolios using the following performance measurements:

Sharpe's Measure (S_P)

$$S_P = \frac{\overline{r}_P - \overline{r}_f}{\sigma_P} \tag{11.1}$$

Measures reward to volatility trade-off by dividing the sample period arithmetic average portfolio excess return by the standard deviation of the portfolio returns. Sharpe's measure is an absolute performance measurement, where the benchmark is a risk-free placement alternative. A higher ratio indicates better risk-adjusted return.

Modigliani-Squared (M^2)

$$M^2 = (S_p - S_M)\sigma_M \tag{11.2}$$

While we can use Sharpe's measure to rank portfolios performance, it is not easy to interpret the values. M^2 is an equivalent representation of Sharpe's measure and focuses on total volatility as a measure of risk, but it has an easier interpretation: The M^2 is the differential return relative to the benchmark index (the market) and lets us quantify the increase in Sharpe in units of percent return.

Jensen's Measure (J_P)

$$J_P = \alpha_P = \overline{r}_P - [\overline{r}_f + \beta_P(\overline{r}_M - \overline{r}_f)] \tag{11.3}$$

Measures portfolio return above the return predicted by the CAPM given the portfolio's beta and average market return. Jensen's measure is the portfolio's alpha value. A higher alpha indicates better risk-adjusted return.

Treynor's Measure (T_P)

$$T_P = \frac{\overline{r}_P - \overline{r}_f}{\beta_P} \tag{11.4}$$

Measures reward to systematic risk trade-off by dividing the sample period arithmetic average portfolio excess return by the beta of the portfolio returns. A higher ratio indicates better risk-adjusted return.

Adjusted Treynor (T_P^*)

$$T_P^* = \frac{\alpha_P}{\beta_P} \tag{11.5}$$

One can obtain the adjusted Treynor by subtracting the markets excess return. This measures how the alpha (Jensen's measure) relates to the portfolios systematic risk (beta).

Appraisal Ratio (AR_P)

$$AR_P = \frac{\alpha_P}{\sigma_{\varepsilon,P}} \tag{11.6}$$

where:

$$\sigma_{\varepsilon,P}^2 = \sigma_P^2 - \beta_P^2 \sigma_{bm}^2 \quad (residual\ risk) \tag{11.7}$$

Dividing the alpha by the unsystematic risk component (residual risk) of the portfolio yields the appraisal ratio. It measures abnormal returns per unit of risk that could be diversified away by holding the market portfolio. A higher ratio indicates better risk-adjusted return.

Information Ratio (IR_P)

$$IR_P = \frac{\overline{r}_P - \overline{r}_{bm}}{\sigma_{P-bm}} \tag{11.8}$$

where

$$\sigma_{P-bm}^2 = \sigma_{\varepsilon,P}^2 + (\beta_P - 1)^2 \sigma_{bm}^2 \quad (tracking\ error) \tag{11.9}$$

Dividing the excess return of a portfolio by the standard deviation of the differences between returns of the portfolio and the returns of the benchmark (tracking error) yields the information ratio. A higher ratio indicates better risk-adjusted return and can be achieved by having a high return in the portfolio, a low return of the benchmark and a low $\sigma_{\mathrm{p-bm}}$.

Risk-Free Rate

A risk-free rate is needed to calculate performance measurements. As the risk-free rate, r_f, we will use the rate of a 3-month government treasury bill issued by the Swedish National Debt Office. An investment in a short-term Swedish governmental debt instrument can be seen as a safe and liquid investment. To get to the rate, we downloaded daily interest data from 01.01.2010 until 31.12.2013[38] and averaged it over the period.

The annualized risk-free rate is $\mathbf{1.085}\%$

[38] Source: Thomson Reuters

Benchmark

To properly assess the performance of a portfolio, it is crucial to select a comparable benchmark. The benchmark should be easy to identify, possible to invest in and be as similar as possible in its risk profile and investment universe to the portfolio we want to measure it against. The benchmark should always be identified *before* starting to measure relative performance to avoid cherry picking.

We compare our portfolios against NASDAQ OMX All-Share Index, consisting of all the shares noted on the NASDAQ OMX Stockholm Stock Market. This index will be used in calculating the performance measurements and represents both our benchmark and the market. In addition, when presenting annualized return and risk, we include comparisons against NASDAQ OMX Stockholm 30 Index that consists of the 30 most actively traded stocks in the Swedish stock market.

7.2 Portfolio Testing & Performance

Following the method described above, we constructed our optimal insider portfolios and back-tested them. In this section, we present our test results and the performance of the portfolios compared to our benchmark.

7.2.1 Portfolio #1

A valid insider signal is when an insider trade is done with a large relative trade volume in a small or mid cap company. We observed 831 valid signals in 164 different companies between 2010-2014.

Descriptive statistics - Portfolio #1

	1-month holding period			2-month holding period		
	Average	**Min**	**Max**	**Average**	**Min**	**Max**
#of shares	12	1	30	23	1	41

Table 28 - Descriptive statistics portfolio #1

Table 28 shows the distribution of shares in the 1-month and 2-month HP portfolios. For the 1-month holding period portfolio, the average number of shares in the portfolio is 12 and the maximum number of shares is 30. For the 2-month holding period portfolio, the average number of shares increases to 23, while the maximum number of shares increases to 41.

Risk and return - Portfolio #1

	1 month HP portfolio	2 month HP portfolio	OMX ALL	OMX 30
R_A	17.91 %	9.13 %	10.36 %	9.58 %
R_G	14.46 %	8.09 %	9.06 %	8.45 %
σ	19.88 %	20.75 %	19.32 %	20.22 %
r_f	1.085%	1.085%	1.085%	1.085%

Table 29 - Risk and return, portfolio #1

The annualized return of Portfolio #1 is 17.91% when the holding period of shares is one month and 9.13% when the holding period is two months. The returns of the OMX All-Share Index is 10.36% and the OMX 30 Index is 9.58%. The annualized standard deviation of Portfolio #1 is 19.88% for a holding period of one month, while it increases to 20.75% when the holding period is two months. The risks, as measured by the standard deviation, are almost the same for the portfolios and the benchmarks.

In Figure 17 below we can see that the one-month holding period outperforms the benchmark during 2010-2014, while the two-month holding period underperforms.

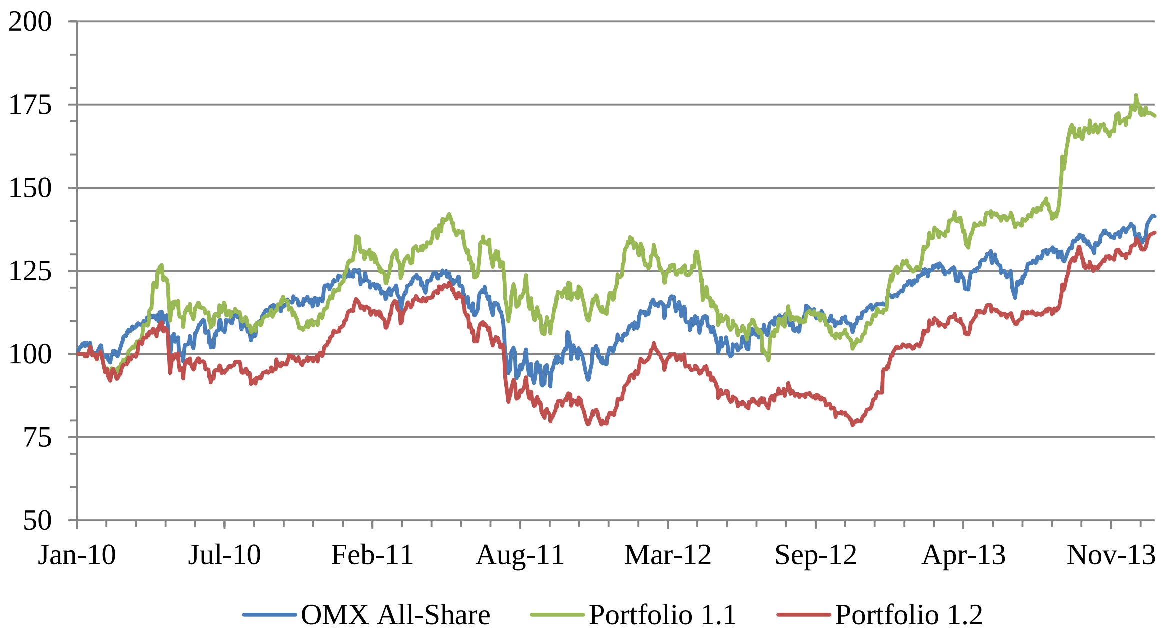

Figure 17 - Portfolio #1 test results

The performance measurements for these portfolios are presented in Table 30.

Performance measurement - Portfolio #1

	1 month HP portfolio	2 month HP portfolio	OMX ALL
Sharpe ratio	0.85	0.39	0.48
M^2	7.08 %	-1.79 %	-
β	0.86	0.93	1.00
Treynor	19.56 %	8.61 %	9.28 %
Adjusted Treynor	10.28 %	-0.66 %	-
Jensen's α	8.85 %	-0.62 %	-
AR	0.81	-0.06	-
$\sigma_{\varepsilon p}$	10.90 %	10.27 %	-
IR	0.67	-0.12	-
$\sigma_{p\text{-}bm}$	11.23 %	10.35 %	-
Adj R^2	0.70	0.76	-

Table 30 - Performance measurements, portfolio #1

1-month HP Portfolio

With a Sharpe ratio of 0.85, the 1-month portfolio indicate better risk-adjusted return than the benchmark, with a ratio of 0.48. The Sharpe ratios cannot be compared directly, thus to relate the Sharpe ratios of the portfolio and the benchmark, we turn to M^2. Measuring the difference in Sharpe ratios on the same level of total risk, the M^2 is easier to interpret as it enables us to quantify the difference in Sharpe. According to M^2, our portfolio would have *outperformed* the OMX All-Share with 7% annually.

However, neither the Sharpe ratio nor M^2 incorporates that our portfolios are undiversified and more exposed to unsystematic risk. The portfolio has a beta of 0.86, implying that for a market return of 1%, the portfolio would have a return of 0.86%. To quantify the relationship between the portfolio return and its beta value, we calculate the Treynor ratio. The portfolio shows a Treynor of 19.56%, meaning that for each additional unit of market risk the portfolio gains 19.56% in excess return above the risk-free rate. Adjusting the Treynor ratio, we find that the portfolio *outperforms* the market by 10.28% for each unit of market risk.

Calculating Jensen's alpha let us investigate the risk and return of the portfolio beyond the market level. We find the alpha of the portfolio to be 8.85%. The *positive* alpha value implies that our portfolio has earned a return above the expected return of the CAPM. To further decompose the composition of risk in our portfolio, we calculate the Appraisal Ratio and Information Ratio that incorporates the residual risk and tracking error.

We find an IR of 0.67, indicating that our portfolio obtained a *positive* active return for the active risk it took compared to the benchmark. The Appraisal Ratio adjusts the Information Ratio to a level where beta is equal to one. Our portfolio has an AR of 0.81, meaning that our portfolio *earns* an alpha of 0.81% for each additional unit of active risk. This means that by actively investing, the portfolio *gained* 0.81% compared to the benchmark.

The adjusted R^2 is a statistical measure of how active a portfolio is. In simple terms, it quantifies how much of the variability in the returns of our portfolio is explained by the variability in the returns of the benchmark. An R^2 of 70% shows that our portfolio has similar variations as the benchmark, indicating that our choice of benchmark is appropriate. Even though, when we measure AR and IR, we find residual risk ($\sigma_{\epsilon p}$) and tracking error (σ_{p-bm}) of around 11%. This indicates that the active risk in our portfolio constitutes a large share of total risk.

2-month HP Portfolio

With a Sharpe ratio of 0.39, the 2-month portfolio indicate worse risk-adjusted return than the benchmark. From the M^2 we can see that our portfolio would have *underperformed* the OMX All-Share Index with 1.79% annually.

The portfolio has a beta of 0.93, implying that for a market return of 1%, the portfolio would have a return of 0.93%. The portfolio shows a Treynor ratio of 8.61%, meaning that for each additional unit of market risk the portfolio gains 8.61% in excess return above the risk free rate. Adjusting the Treynor ratio, we find that the portfolio *underperforms* the market by 0.66% for each unit of market risk. We find the alpha of the portfolio to be -0.62%. The *negative* alpha value implies that our portfolio has earned a return below the expected return of the CAPM. We calculate an IR of -0.12, indicating that our portfolio obtained a *negative* active return for the active risk it took compared to the benchmark. Our portfolio has an AR of -0.06, meaning that our portfolio *looses* an alpha of 0.06% for each additional unit of active risk. This means that by actively investing, the portfolio *lost* 0.06% compared to the benchmark.

An R^2 of 76% shows that our portfolio has similar variations as the benchmark, indicating that our choice of benchmark is appropriate. Even though, when we measure AR and IR, we find residual risk ($\sigma_{\epsilon p}$) and tracking error (σ_{p-bm}) of around 10%, indicating that the active risk in our portfolio constitutes a large share of total risk.

7.2.2 Portfolio #2

A valid insider signal is when an insider trade is done with a small absolute trade volume in a small or mid cap company. In total we observed 244 valid signals in 93 different companies.

Descriptive statistics - Portfolio #2

	1-month holding period			2-month holding period		
	Average	**Min**	**Max**	**Average**	**Min**	**Max**
# of shares	4	1	10	7	1	15

Table 31 - Descriptive statistics portfolio #2

Risk and return - Portfolio #2

	1 month HP portfolio	2 month HP portfolio	OMX ALL	OMX 30
R_A	12.98 %	8.90 %	10.36 %	9.58 %
R_G	11.02 %	7.91 %	9.06 %	8.45 %
σ	38.82 %	34.05 %	19.32 %	20.22 %
r_f	1.085%	1.085%	1.085%	1.085%

Table 32 - Risk and return, portfolio #2

The annualized return of Portfolio #1 is 12.98% when the holding period of shares is one month. When the holding period is increased to two months, the annualized return decreases to 8.90%. The annualized standard deviation of Portfolio #1 is 38.82% for a holding period of one month, while it decreases to 34.05% when the holding period increases to two months.

In Figure 18 we can see that the 1-month holding period portfolio outperforms the benchmark during 2010-2014, although underperforming for nearly the first three years. The 2-month holding period portfolio underperforms.

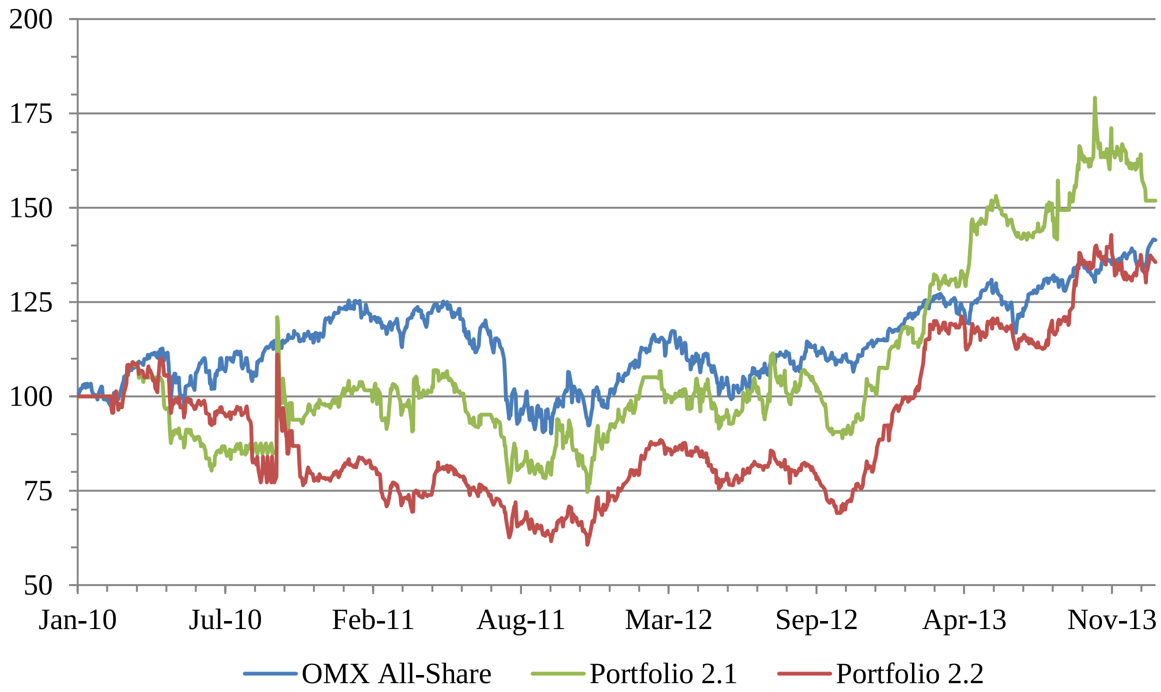

Figure 18 - Portfolio #2 test results

The performance measurements for these portfolios are presented in Table 33.

Performance measurement - Portfolio #2

	1 month HP portfolio	2 month HP portfolio	OMX ALL
Sharpe ratio	0.31	0.23	0.48
M^2	-3.36 %	-4.85 %	-
β	1.67	1.20	1.00
Treynor	7.14 %	6.49 %	9.28 %
Adjusted Treynor	-2.14 %	-2.79 %	-
Jensen's α	-3.57 %	-3.35 %	-
AR	-2.00	-1.94	-
$\sigma_{\varepsilon p}$	21.70 %	24.88 %	-
IR	0.10	-0.06	-
$\sigma_{p\text{-}bm}$	25.23 %	25.22 %	-
Adj R^2	0.69	0.47	-

Table 33 - Performance measurements, portfolio #2

1-month HP Portfolio

Due to high standard deviation in the portfolio, we get a Sharpe ratio of 0.31, below the Sharpe ratio of the benchmark. From the M^2 we can see that our portfolio would have *underperformed* the OMX All-Share with 3.36% annually. The portfolio has a beta of 1.67, implying that for a market return of 1%, the portfolio would have a return of 1.67%. The portfolio shows a Treynor ratio of 7.14%. Adjusting the Treynor ratio, we find that the portfolio *underperforms* the market by 2.14% for each unit of market risk.

We find the alpha of the portfolio to be -3.57%. The *negative* alpha value implies that our portfolio has earned a return below the expected return of the CAPM. We calculate an IR of 0.10, indicating that our portfolio obtained a *positive* active return for the active risk it took compared to the benchmark. Our portfolio has an AR of -2.00, meaning that our portfolio *looses* an alpha of 2.00% for each additional unit of active risk taken.

An R^2 of 69% shows that our portfolio has similar variations as the benchmark, indicating that our choice of benchmark is appropriate. Still, by measuring AR and IR, we find residual risk ($\sigma_{\epsilon p}$) and tracking error (σ_{p-bm}) of 22% and 25% indicating that the active risk in our portfolio constitutes a large share of total risk.

2-month HP Portfolio

Shows a Sharpe ratio of 0.23, below the benchmark. M^2 shows that our portfolio would have *underperformed* the OMX All-Share with 4.85% annually. The portfolio has a beta of 1.20, implying that for a market return of 1%, the portfolio would have a return of 1.20%. The portfolio shows a Treynor ratio of 6.49%. Adjusting the Treynor ratio, we find that the portfolio *underperforms* the market by 2,79% for each unit of market risk.

We find the alpha of the portfolio to be -3,35%. The *negative* alpha value implies that our portfolio has earned a return below the expected return of the CAPM. We calculate an IR of -0.06, indicating that our portfolio obtained a *negative* active return for the active risk it took compared to the benchmark. Our portfolio has an AR of -1.94, meaning that our portfolio *looses* an alpha of 1.94% for each additional unit of active risk.

An R^2 of 47% shows that our portfolio does not display similar variations as the benchmark, indicating a poor choice of benchmark. When we measure AR and IR, we find residual risk ($\sigma_{\epsilon p}$) and tracking error (σ_{p-bm}) of approximately 25% indicating that the active risk in our portfolio constitutes a large share of total risk.

7.2.3 Portfolio #3

A valid insider signal is when a trade is done by a Managing Director. In total we observed 527 valid signals in 145 different companies over the period.

Descriptive statistics - Portfolio #3

	1-month holding period			2-month holding period		
	Average	Min	Max	Average	Min	Max
# of shares	8	1	19	15	1	29

Table 34 - Descriptive statistics portfolio #3

Risk and return - Portfolio #3

	1 month HP portfolio	2 month HP portfolio	OMX ALL	OMX 30
R_A	10.80 %	18.63 %	10.36 %	9.58 %
R_G	9.39 %	14.94 %	9.06 %	8.45 %
σ	24.27 %	19.40 %	19.32 %	20.22 %
r_f	1.085%	1.085%	1.085%	1.085%

Table 35 - Risk and return, portfolio #3

The annualized return of Portfolio #3 is 10.80% when the holding period of shares is one month. When the holding period is increased to two months, the annualized return increases to 18.63%. The annualized standard deviation of Portfolio #1 is 24.27% for a holding period of one month, while it decreases to 19.40% when the holding period increases to two months. From Figure 19 below, we can see that the both portfolios outperform the benchmark over the period.

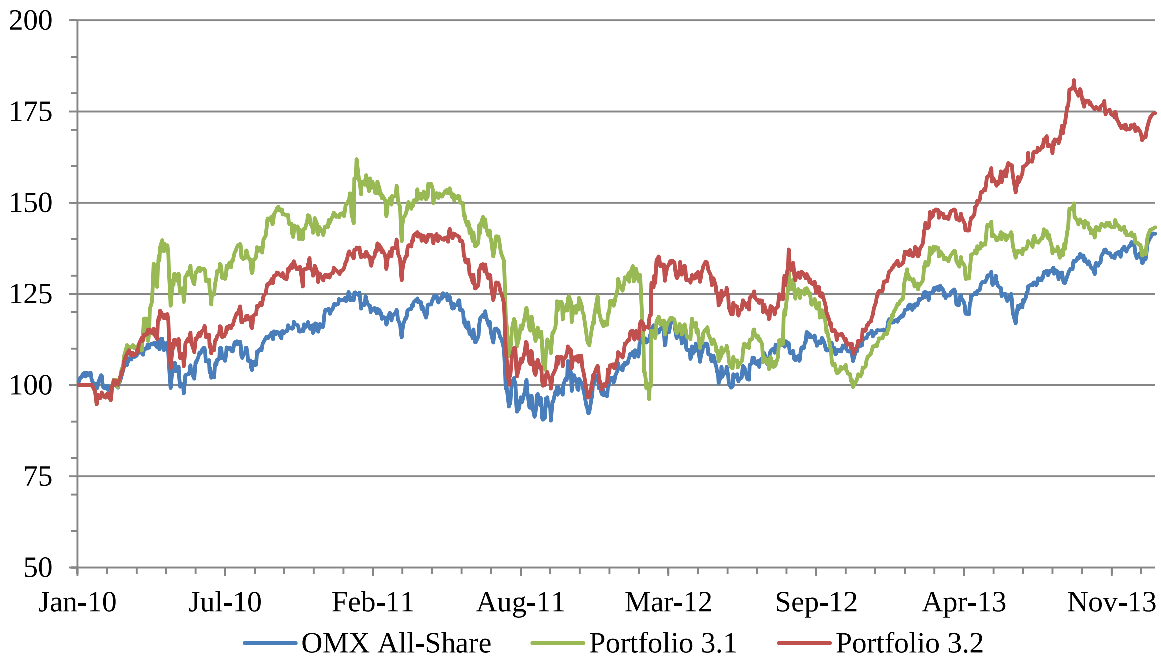

Figure 19 - Portfolio #3 test results

The performance measurements for these portfolios are presented in Table 36.

	Performance measurement - Portfolio #3		
	1 month HP portfolio	**2 month HP portfolio**	**OMX ALL**
Sharpe ratio	0.40	0.90	0.48
M^2	-1.54 %	8.20 %	-
β	0.86	0.94	1.00
Treynor	11.33 %	18.69 %	9.28 %
Adjusted Treynor	2.05 %	9.41 %	-
Jensen's α	1.76 %	8.84 %	-
AR	6.44	2.12	-
$\sigma_{\varepsilon p}$	17.74 %	6.89 %	-
IR	0.02	1.18	-
$\sigma_{p\text{-}bm}$	17.95 %	7.00 %	-
Adj R^2	0.47	0.87	-

Table 36 - Performance measurements, portfolio #3

1-month HP Portfolio

With a Sharpe ratio of 0.40, the 1-month portfolio indicate worse risk-adjusted return than the benchmark. From the M^2 we can see that our portfolio would have *underperformed* the OMX All-Share with 1.54% annually.

The portfolio has a beta of 0.86, implying that for a market return of 1%, the portfolio would have a return of 0.86%. The portfolio shows a Treynor ratio of 11.33%. Adjusting the Treynor ratio, we find that the portfolio *outperforms* the market by 2.05% for each unit of market risk.

We find the alpha of the portfolio to be 2%. The *positive* alpha value implies that our portfolio has earned a return above the expected return of the CAPM. We calculate an IR of 0.02, indicating that our portfolio obtained a *positive* active return for the active risk it took compared to the benchmark. Our portfolio has an AR of 6.44, meaning that our portfolio *earns* an alpha of 6.44% for each additional unit of active risk.

An R^2 of 47% shows that our portfolio does not display similar variations as the benchmark, indicating a poor choice of benchmark. AR and IR shows a residual risk ($\sigma_{\epsilon p}$) and tracking error (σ_{p-bm}) of approximately 18%, indicating that the active risk in our portfolio constitutes a large share of total risk.

2-month HP Portfolio

With a Sharpe ratio of 0.90, the 2-month portfolio indicate greater risk-adjusted return than the benchmark. From the M^2 we can see that our portfolio would have *outperformed* the OMX All-Share with 8% annually.

The portfolio has a beta of 0.94, implying that for a market return of 1%, the portfolio would have a return of 0.94%. The portfolio shows a Treynor ratio of 18.69%. Adjusting the Treynor ratio, we find that the portfolio *outperforms* the market by 9.41% for each unit of market risk.

We find the alpha of the portfolio to be 8.84%. The *positive* alpha value implies that our portfolio has earned a return above the expected return of the CAPM. We calculate an IR of 1.18, indicating that our portfolio obtained a *positive* active return for the active risk it took compared to the benchmark. Our portfolio has an AR of 2.12. By actively investing, the portfolio *earned* 2.12% compared to the benchmark.

An R^2 of 87% shows that our portfolio has similar variations as the benchmark, indicating that our choice of benchmark is good in terms of variation. Also, when we measure AR and IR, we find residual risk ($\sigma_{\epsilon p}$) and tracking error (σ_{p-bm}) of around 7%. This indicates, as opposed to for other portfolios, that the active risk does not constitute a very large share of total risk.

7.2.4 Discussion of Portfolio Performance

Taking into consideration all the performance measurements, not all portfolios performed as we expected.

Portfolio #1 outperformed the benchmark and exhibits positive performance measurements when the holding period is 1 month. This supports our assumption that insider trades can predict future stock returns. Even though, the relatively high residual risk leads us to believe that these results may be exaggerated and does not represent the realistic risk level of such a portfolio. When measuring the performance of Portfolio #1 with a holding period of two months we find that the portfolio underperforms compared to the benchmark. As the holding period increases and the average number of stocks in the portfolio increase, the portfolio becomes more diversified and one should expect the risk to decrease. This is not the case here. The performance measurements show that the IR becomes negative, implying that the active stock selection of the portfolio generates negative returns compared to the risk taken.

Portfolio #2 performed poorly for both holding periods. Even though the portfolio with a holding period of one month generated higher cumulative returns than the benchmark, the performance measurements paint a different picture. Using M^2, both portfolios underperformed the benchmark when adjusting to the benchmarks risk level. We find that they both have very high standard deviations, tracking errors and residual risk. We believe this can be explained by a low average number of shares in both portfolios, caused by few valid insider signals. Also, the R^2 indicates that the benchmark makes a poor comparison.

Portfolio #3 displays better qualities. With the exception of a negative M^2 for the portfolio with a 1-month holding period, all performance measurements are positive. We find the portfolio with a 2-month holding period to perform exceptionally good. For each unit of risk it outperforms the market by 8%, represented by M^2. In addition, the Information Ratio is exceptionally high. This indicates that the portfolio generates highly positive returns for each unit of active risk taken, supported by the fact that the tracking error is small. In addition this portfolio exhibits signs of relatively good diversification. The average number of shares is high, resulting in both a beta and R^2 close to 1. We see this as an indication that Managing Directors can signal future abnormal returns of their company’s stock.

7.3 Result Critique

The drawbacks of our portfolios relate to the weighting method and the frequency of rebalancing the portfolio, as well as the choice of benchmark and the performance measurements used.

Transaction Costs

Creating realistic portfolios means considering transaction costs. The transaction costs does not only include brokerage commission, but also account expenses and the spread between the bid and ask price. Including transaction costs in our calculations will completely eliminate the return of all the six portfolios as our rebalancing mechanism requires a lot of trading. By adding a transaction cost of 0.4% of the traded value, all our portfolios show worse risk-adjusted returns than the benchmark[39].

Taking into account bid-ask spreads and transaction costs, Seyhun (1986) show that insider trades does not provide significant abnormal returns. Seyhun concludes that outside investors cannot use reported insider trades to earn abnormal profits. Gelband (2005) proved otherwise and showed that deducting transaction costs did not alter the significance of abnormal returns following insider trades.

Benchmark

Although our benchmark contains securities in the same investment universe and seems to vary fairly well with the benchmark[40] represented by a high R^2, the benchmark is very well-diversified compared to our insider portfolios. The diversification in our insider portfolios are weak and contains a lot more unsystematic risk than the impression made by the standard deviation of these portfolios. The comparison is therefore not optimal.

Performance Measurement

Although most of our performance measurements are widely used they still need a long history of return data together with a steady level of performance to be reliable. The measurements do not necessarily provide consistent assessments of performance as risk measures to adjust returns differ.

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[39] In fact, all portfolios show negative returns over the period.

[40] With the exception of portfolio 2.2 and portfolio 3.1,

8. Concluding Remarks

The objective of our study was to empirically analyze if publicly available information on insider trading could give us any insights into where stock prices would head in the future and if outside investors could earn abnormal returns by creating portfolios based on this information. To do so, we performed an event study on 6 627 insider trades on the NASDAQ OMX Stockholm between 2010 and 2014 and on different subsets of this data.

Our results indicate that insiders are better informed about the overall future performance of their company, in line with most previous literature. The evidence support that insider trades reveal information that has a permanent effect on the company's value and that the information is not efficiently handled by the market, suggesting that markets are not semi-strong efficient. Insider sales seem to signal higher abnormal returns than purchases following the insider trade.

When performing our analysis on different data subsets on a firm level, we revealed that there is a negative correlation between abnormal returns and market capitalization. We also find that the market does not efficiently incorporate the present value of growth opportunities and therefore growth companies seem to deliver abnormal returns over value companies. We find, contrary to what we hypothesized, that insider trades in firms with low leverage earn higher abnormal returns than companies with high financial leverage. Further, industries characterized by highly sensitive information such as Health Care and Technology delivers significantly higher abnormal returns than other industries. Insider trade signals are in general weaker in months adjacent to quarterly reports than in months not adjacent to quarterly reports and companies that have experienced momentum the preceding six months have higher abnormal returns than companies that have not.

On the individual level, we find that Managing Directors give the most significant signal, while large shareholders give the least significant. Trades with a small *absolute* volume provide a stronger signal of abnormal returns than large absolute volume insider trades. Trades with a large *relative* volume outperform small relative volume trades.

Based on our findings we created three insider portfolios with two different holding periods to see whether these portfolios were able to deliver risk-adjusted returns over the market. We showed that some portfolios were able to gain risk-adjusted returns above the market, although the return vanished when adding transaction costs. We can therefore not conclude that it is possible for outside investors to profit from following insider-based portfolio strategies.

Further Research

Building on our studies, it would be interesting to look at the abnormal returns of more data subsets. For example looking at the returns following the initial trade of an individual insider versus recurrent trades, or insider trades with a “routine” character (insider trades that are repeated with a regular interval) versus insider trades with a more “opportunistic” character. Combinations of data subsets could also be interesting, e.g. Managing Directors in small cap companies, growth companies with momentum or Technology firms with low leverage. Looking at intraday abnormal returns could be of interest for doing in-depth analysis of how the market responds to and incorporates the publication effect of insider trades. Lastly, it would be of interest to perform similar studies on markets in different countries for comparison.

An extension of our study could incorporate employees without reporting obligations. Employees may possess knowledge about the general state of the company and may be superior in comprehending the value of new information, or they may hold inside information. Even though, only certain employees are obligated to report their transaction. By incorporating both reported insider trades and employee trading (private information), one could get a deeper understanding of the information value resulting from insider trading and one could put strong form market efficiency to the test.

As for the practical approach, there are unlimited possibilities. We find the most important improvement to be the reduction of transaction costs. An alternative could be to assign minimum and maximum weights to the portfolio, in combination with reduced rebalancing. This would dramatically reduce the number of transactions, thus transaction costs. The drawback of such an approach is that not all valid insider signals could be accounted for and lead to portfolio inclusion. As we wanted to perform a general test and incorporate for as many signals as possible, we did not enforce such restrictions.

Literature

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

Agrawal, A., Jaffe, J. and Mandelker, G. (1992). The Post-Merger Performance of Acquiring Firms: A Re-examination of an Anomaly. *Journal of Finance*, 47(4), pp.1605-1621.

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

Bainbridge, S. (2000). *Insider Trading: An Overview*. SSRN Working Paper. California: School of Law: University of California (UCLA).

Banz, R. (1981). The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9(1), pp.3-18.

Barclay, M. and Warner, J. (1993). Stealth trading and volatility: Which trades move prices?. *Journal of Financial Economics*, 34, pp.281-305.

Beny, L. (2005). Do insider trading laws matter? Some preliminary comparative evidence. *American Law and Economics Review*, 7, pp.144-183.

Bernard, V. and Thomas, J. (1989). Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium?. *Journal of Accounting Research*, 27, pp.1-36.

Bessembinder, H. and Chan, K. (1998). Market efficiency and the returns to technical analysis. *Financial Management*, 27(2), pp.5-17.

Bhattacharya, U. and Daouk, H. (2002). The World Price of Insider Trading. *Journal of Finance*, 57(1), pp.75-108.

Brock, W., Lakonishok, J. and LeBaron, B. (1992). Simple Technical Trading Rules and the Stochastic Properties of Stock Returns. *Journal of Finance*, 47(5), pp.1731-1764.

Brown, S. and Warner, J. (1980). Measuring Security Price Performance. *Journal of Financial Economics*, 8, pp.205-258.

Brown, S. and Warner, J. (1985). Using Daily Stock Returns. *Journal of Financial Economics*, 14, pp.3-31.

Brown, S. and Weinstein, M. (1985). Derived Factors in Event Studies. *Journal of Financial Economics*, 14(3), pp.491-495.

Chen, H. and Singal, V. (2004). All things considered, taxes drive the January effect. *Journal of Financial Research*, 27(3), pp.351-372.

Chen, N., Roll, R. and Ross, S. (1986). Economic Forces and the Stock Market. *The Journal of Business*, 59(3), pp.383-403.

Cohen, L., Malloy, C. and Pomorski, L. (2012). Decoding Inside Information. *Journal of Finance*, 67(3), pp.1009-1043.

De Bondt, W. and Thaler, R. (1985). Does the Stock Market Overreact?. *Journal of Finance*, 40(3), pp.793-805.

Eckbo, E. and Smith, D. (1998). The Conditional Performance of Insider Trades. *Journal of Finance*, 53(2), pp.467-498.

Engevik, Ø. and Helleren, O. (2009). *Innsidehandel - En empirisk studie av Oslo Børs*. Master Thesis. Norwegian School of Economics.

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

Fama, E. (1976). *Foundations of Finance*. New York: Basic Books, p.133.

Fama, E. and Blume, M. (1966). Filter Rules and Stock-Market Trading. *The Journal of Business*, 39(1), pp.226-241.

Fama, E. and French, K. (1992). The Cross-Section of Expected Stock Returns. *Journal of Finance*, 47(2), pp.427-465.

Fama, E. and French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33, pp.3-56.

Fama, E., Fisher, L., Jensen, M. and Roll, R. (1969). The Adjustment of Stock Prices to New Information. *International Economic Review*, 10(1), pp.1-21.

Fidrmuc, J., Goergen, M. and Renneboog, L. (2006). Insider Trading, News Releases, and Ownership Concentration. *Journal of Finance*, 61(5), pp.2931-2973.

Gelband, A. (2005). Opportunities After Sarbanes-Oxley: Can Outsiders Earn Abnormal Profits by Mimicking Insider Trades?. *California: Department of Economics, Stanford University*.

Givoly, D. and Palmon, D. (1985). Insider Trading and the Exploitation of Inside Information: Some Empirical Evidence. *The Journal of Business,* 58(1), pp.69-87.

Glass, G. (1966). *Extensive insider accumulation as an indicator of near-term stock price performance*. Ph.D. dissertation. The Ohio State University.

Holen, S. (2008). *Fortjenestepotensialet for innsidehandel på Oslo Børs*. Master Thesis. Norwegian School of Economics.

Huddart, S. and Ke, B. (2007). Information asymmetry and cross-sectional determinants of insider trading. *Contemporty Accounting Reasearch*, 24(1), pp.195-232.

Husøy, P. and Jentoft, N. (2013). *En studie om muligheten til å oppnå unormal avkastning ved å følge rapporterte innsidehandler*. Master Thesis. Handelshøgskolen i Bodø.

Ikenberry, D., Lakonishok, J. and Vermaelen, T. (1995). Market underreaction to open market share repurchases. *Journal of Financial Economics,* 39, pp.181-208.

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

Jegadeesh, N. and Titman, S. (1993). Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. *Journal of Finance*, 48(1), pp.65-91.

Jeng, L., Metrick, A. and Zeckhauser, R. (2003). Estimating the returns to insider trading: A performance-evaluation perspective. *The Review of Economics and Statistics*, 85(2), pp.453-471.

Jensen, M. and Bennington, G. (1970). Random walks and technical theories: Some additional evidence. *Journal of Finance*, 25, pp.469-482.

Jensen, M. and Ruback, R. (1983). The Market For Corporate Control: The Scientific Evidence. *Journal of Financial Economics*, 11, pp.5-50.

Johansson, L. and Knopp, M. (2005). *Insynshandel på den svenska aktiemarknaden*. Master Thesis. Lunds Universitet.

Kallunki, J., Nilsson, H. and Hellström, J. (2009). Why do insiders trade? Evidence based on unique data on Swedish insiders. *Journal of Accounting and Economics*, 48, pp.37-53.

Ke, B., Huddart, S. and Petroni, K. (2003). What insiders know about future earnings and how they use it: evidence from insider trades. *Journal of Accounting & Economics*, 35(3), pp.315-346.

Keown, A. and Pinkerton, J. (1981). Merger Announcements and Insider Trading Activity: An Empirical Investigation. *Journal of Finance*, 36(4), pp.855-869.

Kolasinski, A. and Li, X. (2010). Are corporate managers savvy about their stock price? Evidence from insider trading after earnings announcements. *Journal of Accounting and Public Policy*, 29, pp.27-44.

Kothari, S. and Warner, J. (2006). Econometrics of Event Studies. *New Hampshire: Center For Corporate Governance, Tuck School of Business at Dartmouth*.

Lakonishok, J. and Lee, I. (2001). Are Insider Trades Informative?. *The Review of Financial Studies*, 14(1), pp.79-11.

Lakonishok, J. and Vermaelen, T. (1990). Anomalous Price Behavior Around Repurchase Tender Offers. *Journal of Finance*, 45(2), pp.455-477.

Loughran, T. and Ritter, J. (1995). The New Issues Puzzle. *Journal of Finance*, 50(1), pp.23-51.

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

Manne, H. (1968). Insider Trading and the Stock Market. *The Journal of Business*, 41(2), pp.263-265.

Michaely, R., Thaler, R. and Womack, K. (1995). Price Reactions to Dividend Initiations and Omissions: Overreaction or Drift?. *Journal of Finance*, 50(2), pp.573-608.

Mitchell, M. and Netter, J. (1994). The Role of Financial Economics in Securities Fraud Cases: Applications at the Securities and Exchange Commission. *The Business Lawyer*, 49(2), pp.545-590.

Modigliani, F. and Miller, M. (1958). The Cost of Capital, Corporation Finance and the

Theory of Investment. *The American Economic Review*, 48(3), pp.261-297.

Omsted, H. and Olsen, J. (2014). *Estimating the Returns to Insider Trading on Oslo Børs*. Master Thesis. Norwegian School of Economics.

Peterson, P. (1989). Event Studies: A Review of Issues and Methodology. *Quarterly Journal of Business and Economics*, 28(3), pp.36-66.

Polborn, M., Hoy, M. and Sadanand, A. (2006). Advantageous Effects of Regulatory Adverse Selection in the Life Insurance Market. *The Economic Journal*, 116(508), pp.327-354.

Poterba, J. and Summers, L. (1987). Mean reversion in stock prices: Evidence and implications. *NBER Working Paper Series*, 2343.

Reinganum, M. (1981). The Arbitrage Pricing Theory: Some Empirical Results. *Journal of Finance*, 36(2), pp.313-321.

Rogoff, D. (1964). The forecasting properties of insiders' transactions. *Journal of Finance*, 19(4), pp.697-698.

Ross, S. (1976). The Arbitrage Theory of Capital Asset Pricing. *Journal of Economic Theory*, 13, pp.341-360.

Rozeff, M. and Zaman, M. (1988). Market Efficiency and Insider Trading: New Evidence. *The Journal of Business*, 61(1), pp.25-44.

Scholes, M. and Williams, J. (1977). Estimating Betas from Nonsynchronous Data. *Journal of Financial Economics*, 5(3), pp.309-327.

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

Seyhun, H. (1992). Why Does Aggregate Insider Trading Predict Future Stock Returns. *The Quarterly Journal of Economics*, 107(4), pp.1303-1331.

Seyhun, H. (1998). *Investment Intelligence from Insider Trading*. Cambridge, MA: MIT Press.

Sjöholm, M. and Skoog, P. (2006). *Insider trading on the Stockholm Stock Exchange*. Master Thesis. Stockholm School of Economics.

Statman, M. (1987). How Many Stocks Make a Diversified Portfolio?. *Journal of Financial and Quantitive Analysis*, 22(3), pp.353-363.

Internet

E24.no | Sveriges mektigste familier. 2015. Available at: http://bit.ly/1FsWGP5. Accessed 13 May 2015

NBIM.no | Holdings. 2015. Available at: http://bit.ly/1NtHIgw. Accessed 13 May 2015

U.S Securities and Exchange Commission | Insider Trading. 2015. Available at: http://www.sec.gov/answers/insider.htm. Accessed 01 April 2015.

U.S Securities and Exchange Commission | Insider Trading. 2015. Available at: http://www.sec.gov/answers/insider.htm. Accessed 01 April 2015.

Data

Bloomberg

Dovre Forvaltning

Macrobond

NASDAQ OMX

Swedish Financial Supervisory Authority

Thomson Reuters

Figures and Tables

Figures

Tables

Formulas

1 Measuring abnormal returns

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|APM_t) \tag{1.1}$$

2 Testing framework

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{2.1}$$

3 The Market Model

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \varepsilon_{i,t} \tag{3.1}$$

where:

$R_{i,t}$ = Return on asset i at time t
$R_{M,t}$ = Return on the market portfolio M at time t
α_i = Intercept (the value of R_i when R_M equals zero)
$\beta_{i,M}$ = Slope (estimate of the systematic risk for asset i)
$\varepsilon_{i,t}$ = Regression error with expected value equal to zero (firm-specific surprises)

The OLS estimators of the market model parameters (alfa, beta and the error variance) are:

$$\widehat{\alpha}_i = \widehat{\mu}_i - \widehat{\beta}_{i,M}\widehat{\mu}_M \tag{3.2}$$

$$\widehat{\beta}_{i,M} = \frac{\sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\mu}_i)(R_{M,t} - \widehat{\mu}_M)}{\sum_{t=t_{-130}}^{t_{-10}} (R_{M,t} - \widehat{\mu}_M)^2} \tag{3.3}$$

$$\widehat{\sigma}^2_{\varepsilon,i} = \frac{1}{L_1 - 2} \sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_{i,M} R_{M,t})^2 \tag{3.4}$$

where:

$$\widehat{\mu}_i = \frac{1}{L_1} \sum_{t=t_{-130}}^{t_{-10}} R_{i,t} \tag{3.5}$$

and

$$\widehat{\mu}_M = \frac{1}{L_1} \sum_{t=t_{-130}}^{t_{-10}} R_{M,t} \tag{3.6}$$

4 The Constant Mean Return Model

$$R_{i,t} = \mu_i + \varepsilon_{i,t} \tag{4.1}$$

where

$$E(\varepsilon_{i,t}) = 0 \tag{4.2}$$

and

$$var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon,i} \tag{4.3}$$

$\widehat{\mu}_i$ is estimated by the arithmetic mean of the returns in the chosen estimation window:

$$\widehat{\mu}_i = \frac{1}{L_1} \sum_{t=t_{-130}}^{t_{-10}} R_{i,t} \tag{4.4}$$

5 The Multifactor Model

$$R_{i,t} = \alpha_i + \beta_{i,M} R_{M,t} + \beta_{i,SMB} SMB_t + \beta_{i,HML} HML_t + \varepsilon_{i,t} \tag{5.1}$$

where:

$\beta_{i,SMB}$= Coefficient for SMB (estimate of the size risk for asset i)
SMB_t = Small Minus Big factor
$\beta_{i,HML}$= Coefficient for HML (estimate of the value risk for asset i)
HML_t= High Minus Low factor

The expected value of the error term is zero, i.e. $E(\varepsilon_{i,t} = 0)$ and $Var(\varepsilon_{i,t}) = \sigma^2_{\varepsilon,i}$

The *additional*[2] OLS estimators of the multifactor model parameters are:

$$\widehat{\alpha}_i = \widehat{\mu}_i - \widehat{\beta}_{i,M}\widehat{\mu}_M - \widehat{\beta}_{i,SMB} SMB_t - \widehat{\beta}_{i,HML} HML_t \tag{5.2}$$

$$\widehat{\beta}_{i,SMB} = \frac{\sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\mu}_i)(SMB_t - \widehat{SMB})}{\sum_{t=t_{-130}}^{t_{-10}} (SMB_t - \widehat{SMB})^2} \tag{5.3}$$

$$\widehat{\beta}_{i,HML} = \frac{\sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\mu}_i)(HML_t - \widehat{HML})}{\sum_{t=t_{-130}}^{t_{-10}} (HML_t - \widehat{HML})^2} \tag{5.4}$$

$$\widehat{\sigma}^2_{\varepsilon,i} = \frac{1}{L_1 - 2} \sum_{t=t_{-130}}^{t_{-10}} (R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_{i,M} R_{M,t} - \widehat{\beta}_{i,SMB} SMB_t - \widehat{\beta}_{i,HML} HML_t)^2 \tag{5.5}$$

6 Abnormal returns

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|APM_t) \tag{1.1}$$

$$AR_{i,t} = R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i R_{M,t} \tag{6.1}$$

$$\sigma^2(AR_{i,t}) = \sigma^2_{\varepsilon,i} + \frac{1}{L_1}\left[1 + \frac{(R_{M,t} - \widehat{\mu}_M)^2}{\widehat{\sigma}^2_M}\right] \tag{6.2}$$

As we use a large estimation window, $\frac{1}{L_1}\left[1 + \frac{(R_{M,t} - \widehat{\mu}_M)^2}{\widehat{\sigma}^2_M}\right] \sim 0$

$$\sigma^2(AR_{i,t}) \cong \sigma^2_{\varepsilon,i} \tag{6.3}$$

7 Aggregating abnormal returns across events and time

$$CAR_{i(t_0,t_1)} = \sum_{t=t_0}^{t_1} AR_{i,t} \tag{7.1}$$

$$var(CAR_{i,(t_0,t_1)}) = t_1 \times \sigma^2_{\varepsilon,i} \tag{7.2}$$

$$\overline{AR}_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{7.3}$$

$$var(\overline{AR}_t) = \frac{1}{N^2}\sum_{i=1}^{N} \sigma^2_{\varepsilon,i} \tag{7.4}$$

$$\overline{CAR}_{(t_0,t_1)} = \sum_{t=t_0}^{t_1} \overline{AR}_t \tag{7.5}$$

$$var(\overline{CAR}_{(t_0,t_1)}) = \sum_{t=t_0}^{t_1} var(\overline{AR}_t) \tag{7.6}$$

8 Statistical testing and inference

$$\overline{CAR}_{(t_0,t_1)} \sim N[0, var(\overline{CAR}_{(t_0,t_1)})] \tag{8.1}$$

$$\theta_1 = \frac{\overline{CAR}_{(t_0,t_1)}}{var(\overline{CAR}_{(t_0,t_1)})^{\frac{1}{2}}} \sim N(0,1) \tag{8.2}$$

$$t = \frac{(\overline{CAR}_X - \overline{CAR}_Y) - (\mu_X - \mu_Y)}{\sqrt{\frac{var(\overline{CAR}_{X,(t_0,t_1)})}{n_X} + \frac{var(\overline{CAR}_{Y,(t_0,t_1)})}{n_Y}}} \tag{8.3}$$

$$df = \frac{\left(\frac{var(\overline{CAR}_X(t_o,t_1))}{n_X} + \frac{var(\overline{CAR}_Y(t_o,t_1))}{n_Y}\right)^2}{\frac{\left(\frac{var(\overline{CAR}_X(t_0,t_1))}{n_X}\right)^2}{n_X - 1} + \frac{\left(\frac{var(\overline{CAR}_Y(t_0,t_1))}{n_Y}\right)^2}{n_Y - 1}} \tag{8.4}$$

9 Optimal Insider Portfolio

$$w_{i,t}^{equal} = \frac{1}{N} \quad \forall \quad i \subseteq N \tag{9.1}$$

$$w_{i,t}^{cap} = \frac{C_i}{\sum_{i=1}^{N} C_i} \quad \forall \quad i \subseteq N \tag{9.2}$$

10 Portfolio Risk and Return

$$\sigma_{p,annualized} = \sigma_{p,daily} \times \sqrt{250} \tag{10.1}$$

$$r_{p,t} = \sum_{i=1}^{N} r_{i,t} w_{i,t} \tag{10.2}$$

$$R_p = \sum_{t=1}^{T} r_{p,t} \tag{10.3}$$

$$R_{A,p} = e^{R_p} - 1 \tag{10.4}$$

11 Performance Measurement

$$S_P = \frac{\overline{r}_P - \overline{r}_f}{\sigma_P} \tag{11.1}$$

$$M^2 = (S_p - S_M)\sigma_M \tag{11.2}$$

$$J_P = \alpha_P = \overline{r}_P - [\overline{r}_f + \beta_P(\overline{r}_M - \overline{r}_f)] \tag{11.3}$$

$$T_P = \frac{\overline{r}_P - \overline{r}_f}{\beta_P} \tag{11.4}$$

$$T_P^* = \frac{\alpha_P}{\beta_P} \tag{11.5}$$

$$AR_P = \frac{\alpha_P}{\sigma_{\varepsilon,P}} \tag{11.6}$$

where:

$$\sigma_{\varepsilon,P}^2 = \sigma_P^2 - \beta_P^2 \sigma_{bm}^2 \quad (residual\ risk) \tag{11.7}$$

$$IR_P = \frac{\overline{r}_P - \overline{r}_{bm}}{\sigma_{P-bm}} \tag{11.8}$$

where:

$$\sigma_{P-bm}^2 = \sigma_{\varepsilon,P}^2 + (\beta_P - 1)^2 \sigma_{bm}^2 \quad (tracking\ error) \tag{11.9}$$

Appendix A

Excerpt from raw dataset of reported insider trades

Raw data reported insider trades

Date	Publication date	Company	Ticker	Innsynsperson	Position	Holder	Transaction	Security	Amount	Total	Price	Value	% change
19.12.2012	02.01.2013	AKTIEBOLAGET ELECTROLUX (PUBL)	ELUX.B.ST	Davis, Lorna	Board member	Own	Purchase	Share B	2000	2000	415.91	831828.6	100.00 %
28.12.2012	02.01.2013	WALLENSTAM AB (PUBL)	WALL.B.ST	Gullmarstrand, Anna	Other position	Own	Purchase	Share B	1000	4000	112.59	112588.3	25.00 %
21.12.2012	02.01.2013	RATOS AB (PUBL)	RATO.B.ST	Sšderberg, Jan	Board member, Larger shareholder	Legal person	Purchase	Share B	100000	100000	181.91	18191200	100.00 %
28.12.2012	02.01.2013	GUNNEBO AKTIEBOLAG (PUBL)	GUNN.ST	SVALSTEDT, MARTIN	Board member	Own	Purchase	Share	10000	120000	35.31	353116	8.33 %
27.12.2012	02.01.2013	MIDSONA AB (PUBL)	MSON.B.ST	s•berg, Peter	MD	Own	Purchase	Share B	4485	56637	14.27	63996.465	7.92 %
28.12.2012	02.01.2013	MIDSONA AB (PUBL)	MSON.B.ST	s•berg, Peter	MD	Own	Purchase	Share B	1505	58142	14.49	21800.226	2.59 %
28.12.2012	02.01.2013	MICRONIC MYDATA AB (PUBL)	MICR.ST	BONDE, KATARINA	Board member	Own	Purchase	Share	2000	2000	10.25	20500	100.00 %
20.12.2012	02.01.2013	ODD MOLLY INTERNATIONAL AB (PUBL)	ODD.ST	Arnhult, Rutger	Other position, Larger shareholder	Legal person	Purchase	Share	32571	32571	34.73	1131291.8	100.00 %
28.12.2012	02.01.2013	ODD MOLLY INTERNATIONAL AB (PUBL)	ODD.ST	Arnhult, Mia	Board member, Larger shareholder	Legal person	Purchase	Share	2315	919065	33.60	77775.666	0.25 %
28.12.2012	02.01.2013	ODD MOLLY INTERNATIONAL AB (PUBL)	ODD.ST	Arnhult, Rutger	Other position, Larger shareholder	Legal person	Purchase	Share	2315	919065	33.60	77775.666	0.25 %
27.12.2012	02.01.2013	KAROLINSKA DEVELOPMENT AB	KDEV.ST	Sundstršm, Michael	Other position	Own	Purchase	Share B	4600	4600	14.65	67390	100.00 %
27.12.2012	02.01.2013	KAROLINSKA DEVELOPMENT AB	KDEV.ST	Kalland, Terje	Deputy MD	Own	Purchase	Share B	20000	20000	14.65	293000	100.00 %
27.12.2012	02.01.2013	KAROLINSKA DEVELOPMENT AB	KDEV.ST	Ekstršm, Gunilla	Other position	Own	Purchase	Share B	3550	3650	14.65	52007.5	97.26 %
27.12.2012	02.01.2013	KAROLINSKA DEVELOPMENT AB	KDEV.ST	SternŒs, Ann-Sofie	Other position	Own	Purchase	Share B	4600	4600	14.65	67390	100.00 %
28.12.2012	02.01.2013	KAROLINSKA DEVELOPMENT AB	KDEV.ST	Bjerke, Torbjšrn	MD	Own	Purchase	Share B	30000	41375	15.30	459000	72.51 %
20.12.2012	02.01.2013	HEXAGON AKTIEBOLAG (PUBL)	HEXA.B.ST	Gervide, Anders	Other position	Own	Sale	Share B	-50000	50000	7260.54	363027220	50.00 %
28.12.2012	02.01.2013	ADDTECH AB (PUBL)	ADDT.B.ST	HAGSTEN, G…RAN	Other position subsidiary	Own	Sale	Share B	-2094	11300	294.60	616902.6606	15.63 %
27.12.2012	02.01.2013	EWORK SCANDINAVIA AB (PUBL)	EWRK.ST	CARLING, JIMMIE	Other position	Own	Sale	Share	-7021	8320	42.99	301812.4291	45.77 %
27.12.2012	02.01.2013	KAROLINSKA DEVELOPMENT AB	KDEV.ST	Sundstršm, Michael	Other position	Own	Sale	Share B	-2000	0	14.65	29300	100.00 %
19.12.2012	03.01.2013	ROTTNEROS AB (PUBL)	RROS.ST	Onstad, Thomas	Larger shareholder	Legal person	Purchase	Share	129321	60504490	3.53	456658.3152	0.21 %
20.12.2012	03.01.2013	AB SAGAX (PUBL)	SAGA.A.ST	Arnhult, Rutger	Larger shareholder	Legal person	Purchase	Share A	70542	86638	20.24	1427600.779	81.42 %
03.01.2013	03.01.2013	ARISE WINDPOWER AB (PUBL)	AWP.ST	Nygren, Peter	Board member, MD	Own	Purchase	Share	1369	15369	26.00	35594	8.91 %
21.12.2012	03.01.2013	PHONERA AB (PUBL)	PHON.ST	…jfelth, Robert	MD, Board member subsidiary	Own	Sale	Share	-1500	23607	44.49	66736.95	5.97 %
27.12.2012	03.01.2013	PHONERA AB (PUBL)	PHON.ST	…jfelth, Robert	MD, Board member subsidiary	Own	Sale	Share	-500	23107	43.86	21927.85	2.12 %
27.12.2012	04.01.2013	SKISTAR AKTIEBOLAG (PUBL)	SKIS.B.ST	Paulsson, Mats	Board member, Larger shareholder	Legal person	Purchase	Share B	14058	5490288	148.45	2086867.926	0.26 %
28.12.2012	04.01.2013	BIOTAGE AB (PUBL)	BIOT.ST	Bjšrk, Nils-Olof	Board member	Own	Purchase	Share	1210	17230	9.33	11294.987	7.02 %
27.12.2012	04.01.2013	FINGERPRINT CARDS AB (PUBL)	FING.B.ST	CARLSTR…M, JOHAN	MD, Larger shareholder	Own	Purchase	Share B	40937	303437	12.75	521946.75	13.49 %
28.12.2012	04.01.2013	FINGERPRINT CARDS AB (PUBL)	FING.B.ST	CARLSTR…M, JOHAN	MD, Larger shareholder	Own	Purchase	Share B	70750	374187	12.35	873762.5	18.91 %
27.12.2012	04.01.2013	LAMMHULTS DESIGN GROUP AB (PUBL)	LAMM.B.ST	JOHANSSON ST•HL, ULRIKA	Other position	Spouse	Purchase	Share B	1800	70464	27.73	49916.52	2.55 %
28.12.2012	04.01.2013	PA RESOURCES AKTIEBOLAG (PUBL)	PAR.ST	Bouabbane, Slimane	Other position	Own	Purchase	Share A	30000	39000	55.10	1653000	76.92 %
02.01.2013	04.01.2013	ODD MOLLY INTERNATIONAL AB (PUBL)	ODD.ST	Arnhult, Rutger	Other position, Larger shareholder	Legal person	Purchase	Share	10000	929065	34.73	347331	1.08 %
02.01.2013	04.01.2013	ODD MOLLY INTERNATIONAL AB (PUBL)	ODD.ST	Arnhult, Mia	Board member, Larger shareholder	Legal person	Purchase	Share	10000	929065	34.73	347331	1.08 %

Appendix B

Excerpt from raw dataset of total return

Raw data total return

Ticker	ABB.ST	ACTI.ST	AF-B.ST	ASSA-B.ST	ATCO-A.ST	ATCO-B.ST	ALIV-SDB.ST	BEIJ-B.ST	BBTO-B.ST	BURE.ST
Comp.	ABB Ltd, SEK	Active Biotech AB, SEK	ÅF AB Series B, SEK	Assa Abloy AB Series B, SEK	Atlas Copco AB Series A, SEK	Atlas Copco AB Series B, SEK	Autoliv Inc. SDS, SEK	Beijer Ref AB, SEK	B&B Tools AB, SEK	Bure Equity AB, SEK
01.11.2013	387.62	77.80	123.01	437.73	289.80	266.59	821.07	325.22	175.31	40.42
04.11.2013	389.28	76.99	122.71	434.46	294.20	270.62	829.60	332.39	176.32	39.77
05.11.2013	387.86	76.72	126.04	431.60	292.40	269.11	838.12	337.17	176.32	39.77
06.11.2013	391.18	76.99	126.65	437.46	297.78	273.64	840.96	339.56	181.89	39.77
07.11.2013	391.65	77.26	129.37	446.72	298.27	274.14	831.73	337.17	190.00	40.42
08.11.2013	391.65	77.26	129.68	445.63	296.64	272.13	844.51	341.36	200.13	40.26
11.11.2013	392.12	76.99	130.28	447.13	297.46	273.14	842.38	341.96	217.36	40.26
12.11.2013	394.26	76.45	131.50	444.00	294.69	270.12	843.09	340.76	216.85	40.74
13.11.2013	393.07	74.82	131.50	441.14	295.34	270.45	844.51	315.65	216.85	40.74
14.11.2013	398.05	76.17	133.31	449.31	301.04	276.66	850.19	336.58	219.39	40.58
15.11.2013	397.81	75.90	135.74	450.54	301.86	276.99	855.17	334.18	219.39	41.70
18.11.2013	399.95	74.82	135.74	451.76	304.79	280.18	857.72	338.37	223.44	42.03
19.11.2013	397.34	74.82	134.53	448.63	302.18	276.99	852.00	334.78	221.41	41.70
20.11.2013	394.73	73.73	133.62	450.13	302.02	277.67	849.15	338.37	222.93	41.70
21.11.2013	394.26	73.73	130.59	446.86	300.23	276.32	861.29	333.59	226.48	41.06
22.11.2013	396.39	73.46	129.68	448.90	302.67	280.01	863.43	336.58	226.99	41.70
25.11.2013	396.39	72.65	130.28	451.08	303.98	282.53	867.00	331.20	226.99	41.06
26.11.2013	396.63	75.09	129.68	450.95	302.02	282.03	873.43	333.59	234.08	40.58
27.11.2013	399.24	75.90	129.68	456.12	302.02	282.87	878.43	337.17	233.07	40.90
28.11.2013	397.58	78.34	130.28	452.85	303.00	283.20	874.86	335.98	231.04	41.54
29.11.2013	398.29	80.24	130.59	452.17	297.78	277.83	868.43	339.56	230.03	41.87
02.12.2013	394.97	86.20	130.59	452.99	295.50	276.49	867.71	340.76	233.07	41.87
03.12.2013	385.25	85.39	129.98	443.86	287.68	266.93	852.00	337.17	231.55	41.54
04.12.2013	383.59	81.05	129.37	442.50	286.70	267.77	843.43	341.96	232.05	41.70
05.12.2013	384.30	84.31	129.07	438.55	285.72	267.26	843.43	343.75	233.07	41.22
06.12.2013	390.23	83.76	130.59	439.09	285.40	266.93	850.57	344.35	233.07	41.54
09.12.2013	393.07	82.68	129.68	441.41	286.54	267.60	856.29	330.00	229.01	41.38
10.12.2013	389.28	82.14	129.68	436.10	283.60	264.58	854.86	338.37	226.99	41.38
11.12.2013	388.81	80.78	130.89	438.55	280.99	263.07	844.86	337.77	228.51	41.38
12.12.2013	383.59	77.80	130.28	433.23	278.39	261.06	839.86	334.78	226.48	41.22
13.12.2013	383.35	78.34	129.07	436.10	279.53	262.57	839.86	334.78	233.57	41.22
16.12.2013	388.81	77.26	129.07	447.40	284.09	267.10	843.43	322.83	232.05	41.38
17.12.2013	386.20	75.90	129.98	436.37	277.90	260.72	839.86	319.24	234.08	40.90
18.12.2013	390.94	77.80	129.37	439.50	279.53	261.73	837.00	330.00	234.08	41.06
19.12.2013	398.53	79.16	127.25	450.54	286.86	270.95	842.72	330.00	233.57	41.22
20.12.2013	400.66	75.09	131.50	456.26	286.54	271.12	844.15	318.04	234.08	41.22

Appendix C

Excerpt from cleaned and treated data

Cleaned and treated data

Date	Publication date	Ticker	Position	Transaction	Shares traded	Shares holding	Price	Trade value absolute	Trade value relative	Publication price	Market cap	Firm size	Industry	DE ratio	PE ratio	PB ratio
03.01.2012	02.01.2012	ATEL A	Large shareholder	Purchase	415753	3159293			15.15	26.39	56006721.00	SMALL	Telecommunications		62.87	2.46
03.01.2012	02.01.2012	HUSQ B	Large shareholder	Purchase	200000	460000	34.93	6986040	76.92	36.75	1760000000.00	LARGE	Consumer Goods	1.86	18.33	1.47
03.01.2012	02.01.2012	KAHL	Other position	Sale	-100000	400000	33.86	3386030	20	24.28	216000000.00	MID	Consumer Services	2.71	11.59	0.41
03.01.2012	02.01.2012	LIAB	Other position	Purchase	10000	20000	41.43	414307	100	42.54	339000000.00	MID	Industrials	1.46	30.96	1.04
03.01.2012	02.01.2012	LUND B	Other executive	Purchase	80	125	354.94	28395	177.78	374.81	1770000000.00	LARGE	Financials	0.64	4.93	0.81
03.01.2012	02.01.2012	SAND	Board member parent firm	Purchase	200000	27500000	170.8	34159780	0.73	173.68	13200000000.00	LARGE	Industrials	1.83	18.2	3.08
04.01.2012	03.01.2012	CEVI	Board member parent firm	Purchase	20275	278000	13	263575	7.87	13.5	34721056.00	SMALL	Health Care		21.6	2.51
04.01.2012	03.01.2012	HUSQ B	Large shareholder	Purchase	30000	490000	35.21	1056234	6.52	37.75	1730000000.00	LARGE	Consumer Goods	1.86	18.33	1.47
04.01.2012	03.01.2012	MQ	Board member parent firm	Sale	-10000	0	21.42	214206	100	21.63	81874489.00	SMALL	Consumer Services	0.98	10.75	0.86
04.01.2012	03.01.2012	ORES	Board member parent firm	Purchase	20000	310310	249.96	4999250	6.89	240.74	197000000.00	MID	Financials	0.01	22.75	1.56
04.01.2012	03.01.2012	PACT	Board member parent firm	Sale	-10000	856607	176.88	1768844	1.15	175.2	164000000.00	MID	Technology		60.26	7.19
05.01.2012	04.01.2012	ANOD B	Board member parent firm	Sale	-18000	30000	36.63	659308	37.5	36.44	94622689.00	SMALL	Technology		7.43	1.04
05.01.2012	04.01.2012	PACT	Other position	Purchase	300	400	175.21	52562	300	174.08	163000000.00	MID	Technology		60.26	7.19
05.01.2012	04.01.2012	SKIS B	Large shareholder	Purchase	45000	291025	130.38	5867231	18.29	142.51	379000000.00	MID	Consumer Services	2.37	18.26	2.64
05.01.2012	04.01.2012	SKIS B	Board member parent firm	Purchase	285000	5476230	130.38	37159127	5.49	142.51	379000000.00	MID	Consumer Services	2.37	18.26	2.64
05.01.2012	04.01.2012	SKIS B	Board member parent firm	Purchase	375000	6608281	130.38	48893588	6.02	142.51	379000000.00	MID	Consumer Services	2.37	18.26	2.64
05.01.2012	04.01.2012	SKIS B	Large shareholder	Purchase	45000	320225	130.38	5867231	16.35	142.51	379000000.00	MID	Consumer Services	2.37	18.26	2.64
05.01.2012	04.01.2012	SOBI	Other position	Purchase	1076	3913	14.7	15817	37.93	15.5	483000000.00	MID	Health Care	0.33	144.45	0.81
05.01.2012	04.01.2012	SOBI	Other position	Purchase	993	3543	14.7	14597	38.94	15.5	483000000.00	MID	Health Care	0.33	144.45	0.81
05.01.2012	04.01.2012	SWEC B	Other position	Purchase	1013	2703	83.04	84120	59.94	84.78	549000000.00	MID	Industrials	1.81	14	3.46
06.01.2012	05.01.2012	ECEX	Other position	Purchase	10786	7000	53.56	577725	60.64	53.76	180000000.00	MID	Financials	0.03	12.27	0.69
06.01.2012	05.01.2012	ORES	Board member parent firm	Purchase	40000	350310	254.73	10189384	12.89	240.09	198000000.00	MID	Financials	0.01	22.75	1.56
10.01.2012	09.01.2012	FING B	Managing Director	Sale	-301000	260000	9.68	2914683	53.65	8.15	52748944.00	SMALL	Industrials		120.27	3.82
10.01.2012	09.01.2012	KAHL	Other position	Sale	-52000	400000	35.27	1834217	11.5	25.07	225000000.00	MID	Consumer Services	2.71	11.59	0.41
10.01.2012	09.01.2012	NSP B	Large shareholder	Purchase	35793	64337	8.58	306925	125.4	8.7	12111882.00	SMALL	Consumer Services		45.42	0.76
10.01.2012	09.01.2012	PACT	Managing Director	Sale	-20105	138685	174.09	3499991	12.66	176.32	166000000.00	MID	Technology		60.26	7.19
10.01.2012	09.01.2012	PART	Other position	Purchase	3000	6200	23.46	70393	93.75	23.03	30562693.00	SMALL	Industrials		50.58	0.5
10.01.2012	09.01.2012	SKA B	Other position	Sale	-836	1717	248.49	207737	32.75	252.06	5300000000.00	LARGE	Industrials	2.97	6.19	2.42
11.01.2012	10.01.2012	FING B	Board member parent firm	Sale	-30000	0	8.15	244500	100	7.85	50953246.00	SMALL	Industrials		120.27	3.82
11.01.2012	10.01.2012	REJL B	Board member parent firm	Sale	-1040	599960	76.98	80063	0.17	76.39	82955061.00	SMALL	Industrials		10.8	2.22
11.01.2012	10.01.2012	SWEC B	Large shareholder	Purchase	20000	5027941	85.24	1704898	0.4	87.76	548000000.00	MID	Industrials	1.81	14	3.46
11.01.2012	10.01.2012	SWEC B	Large shareholder	Purchase	20000	5027941	85.24	1704898	0.4	87.76	548000000.00	MID	Industrials	1.81	14	3.46

Appendix D

<u>Primary insider categories</u>

We have categorized our primary insiders into the following six categories:

(1) Managing Director
(2) Board member parent firm
(3) Alternate and/or subsidiary board member
(4) Large shareholder
(5) Other executive
(6) Other position.

The number indicate the priority of which category the insider is put in.

The insider types under each category is how the insider type was presented in the raw data before we assigned them to the mentioned categories.

Managing Director
Alt. board member parent firm, MD
Alt. board member parent firm, MD, MD subsidiary
Board member parent firm, MD parent firm
Board member, Board member parent firm, MD parent firm
Board member, Larger shareholder, Board member parent firm, MD parent firm
Board member, MD
Board member, MD parent firm
Board member, MD, Board member parent firm, MD parent firm
Board member, MD, Board member subsidiary
Board member, MD, Board member subsidiary, MD subsidiary
Board member, MD, Larger shareholder
Board member, MD, Larger shareholder, Board member subsidiary
Board member, MD, Larger shareholder, Board member subsidiary, MD subsidiary
Board member, MD, Other position
Board member, MD, Other position, Larger shareholder
Larger shareholder, Board member parent firm, MD parent firm
MD
MD, Board member subsidiary
MD, Board member subsidiary, Alt. board member subsidiary, MD subsidiary
MD, Board member subsidiary, MD subsidiary
MD, Larger shareholder
MD, Larger shareholder, Board member subsidiary
MD, MD subsidiary
MD, Other position
MD, Other position, Board member subsidiary

Board member parent firm
Board member
Board member parent firm
Board member, Board member parent firm
Board member, Board member subsidiary
Board member, Board member subsidiary, Alt. board member subsidiary, MD subsidiary
Board member, Board member subsidiary, MD subsidiary
Board member, Deputy MD, Board member subsidiary, MD subsidiary
Board member, Deputy MD, Larger shareholder, Board member subsidiary, MD subsidiary
Board member, Larger shareholder
Board member, Larger shareholder, Board member parent firm
Board member, Larger shareholder, Board member parent firm, Deputy MD parent firm
Board member, Larger shareholder, Board member subsidiary
Board member, Larger shareholder, Larger shareholder
Board member, Larger shareholder, MD subsidiary
Board member, MD subsidiary
Board member, Other position
Board member, Other position parent firm
Board member, Other position, Larger shareholder
Larger shareholder, Board member parent firm

Other executive
Larger shareholder, MD subsidiary
Other position, Larger shareholder, MD subsidiary
Deputy MD
Deputy MD subsidiary
Deputy MD subsidiary, Other position subsidiary
Deputy MD, Deputy MD subsidiary
Deputy MD, Deputy MD subsidiary, Other position subsidiary
Deputy MD, MD subsidiary
Deputy MD, MD subsidiary, Deputy MD subsidiary, Other position subsidiary
Deputy MD, Other position
Deputy MD, Other position subsidiary
MD subsidiary
MD subsidiary, Other position subsidiary
Other position, MD subsidiary
Other position, MD subsidiary, Other position subsidiary

Large shareholder
Larger shareholder
Larger shareholder, Other position subsidiary
Other position, Larger shareholder
Other position, Larger shareholder, Other position subsidiary

Other positions
Other position parent firm
Other position subsidiary
Other position subsidiary, Other position subsidiary
Other position, Other position subsidiary
Other position

Alternate and/or subsidiary board member
Alt. board member parent firm
Alt. board member parent firm, Deputy MD
Alt. board member parent firm, Larger shareholder
Alt. board member subsidiary
Alt. board member subsidiary, Deputy MD subsidiary
Alt. board member subsidiary, Other position subsidiary
Alternate board member
Other position, Alt. board member subsidiary
Other position, Board member subsidiary
Other position, Board member subsidiary, Alt. board member subsidiary, MD subsidiary
Other position, Board member subsidiary, Deputy MD subsidiary
Other position, Board member subsidiary, Deputy MD subsidiary, Other position subsidiary
Other position, Board member subsidiary, MD subsidiary
Other position, Board member subsidiary, MD subsidiary, Other position subsidiary
Other position, Board member subsidiary, Other position subsidiary
Board member subsidiary
Board member subsidiary, Deputy MD subsidiary
Board member subsidiary, MD subsidiary
Board member subsidiary, MD subsidiary, Other position subsidiary
Board member subsidiary, Other position subsidiary
Board member subsidiary, Other position subsidiary, Other position subsidiary
Larger shareholder, Board member subsidiary
Deputy MD, Board member subsidiary
Deputy MD, Board member subsidiary, Deputy MD subsidiary
Deputy MD, Board member subsidiary, MD subsidiary
Deputy MD, Other position, Board member subsidiary

Appendix E

Statistics from hypotheses testing: This appendix will include the cumulative average abnormal return ($\overline{CAR}$), the standard deviation (σ) and the p-value across our selected horizon and our three respective models for all our hypotheses. We also include statistics for differences in means.

Hypothesis 1.1-1.3 – Market Level

All trades

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.17 %***	0.028 %	< 0.001	0.18 %***	0.030 %	< 0.001	0.18 %***	0.028 %	< 0.001
1M	0.91 %***	0.124 %	< 0.001	0.83 %***	0.134 %	< 0.001	0.94 %***	0.124 %	< 0.001
2M	1.71 %***	0.175 %	< 0.001	2.07 %***	0.190 %	< 0.001	1.62 %***	0.176 %	< 0.001
3M	2.55 %***	0.215 %	< 0.001	2.81 %***	0.233 %	< 0.001	2.37 %***	0.215 %	< 0.001
6M	4.21 %***	0.304 %	< 0.001	4.91 %***	0.329 %	< 0.001	3.79 %***	0.305 %	< 0.001
n	6627			6627			6627		

	Sales > purchases		
	t	**df**	**P-value**
1D	-25.28	3289	1.000
1M***	21.43	3292	< 0.001
2M***	14.19	3289	< 0.001
3M***	34.21	3288	< 0.001
6M***	90.62	3289	< 0.001

Purchases

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.18 %***	0.034 %	< 0.001	0.21 %***	0.037 %	< 0.001	0.19 %***	0.034 %	< 0.001
1M	0.88 %***	0.154 %	< 0.001	0.62 %***	0.167 %	< 0.001	0.90 %***	0.154 %	< 0.001
2M	1.67 %***	0.217 %	< 0.001	1.80 %***	0.236 %	< 0.001	1.58 %***	0.217 %	< 0.001
3M	2.45 %***	0.266 %	< 0.001	2.28 %***	0.290 %	< 0.001	2.40 %***	0.266 %	< 0.001
6M	3.85 %***	0.375 %	< 0.001	3.93 %***	0.409 %	< 0.001	3.49 %***	0.377 %	< 0.001
n	4479			4479			4479		

Sales

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	-0.15 %***	0.047 %	0.002	-0.12 %**	0.050 %	0.016	0.16 %***	0.047 %	< 0.001
1M	-0.99 %***	0.210 %	< 0.001	-1.27 %***	0.225 %	< 0.001	1.01 %***	0.211 %	< 0.001
2M	-1.77 %***	0.296 %	< 0.001	-2.63 %***	0.318 %	< 0.001	1.71 %***	0.298 %	< 0.001
3M	-2.75 %***	0.363 %	< 0.001	-3.92 %***	0.390 %	< 0.001	2.31 %***	0.365 %	< 0.001
6M	-4.97 %***	0.513 %	< 0.001	-6.96 %***	0.551 %	< 0.001	4.42 %***	0.517 %	< 0.001
n	2148			2148			2148		

Hypothesis 2.1 – Market Capitalization

Large cap

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.08 %**	0.035 %	0.017	0.09 %**	0.045 %	0.047	0.07 %**	0.035 %	0.043
1M	0.72 %***	0.156 %	< 0.001	0.16 %	0.203 %	0.441	0.68 %***	0.156 %	< 0.001
2M	0.87 %***	0.220 %	< 0.001	1.14 %***	0.287 %	< 0.001	0.84 %***	0.221 %	< 0.001
3M	1.40 %***	0.270 %	< 0.001	0.88 %**	0.352 %	0.013	1.31 %***	0.271 %	< 0.001
6M	2.75 %***	0.382 %	< 0.001	2.36 %***	0.498 %	< 0.001	2.50 %***	0.383 %	< 0.001
n	2068			2068			2068		

	Small > Large		
	t	**df**	**P-value**
1D***	199.58	3821	< 0.001
1M***	149.40	3825	< 0.001
2M***	237.33	3826	< 0.001
3M***	233.03	3824	< 0.001
6M***	208.81	3828	< 0.001

Mid cap

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.05 %	0.048 %	0.280	0.08 %	0.051 %	0.133	0.08 %*	0.048 %	0.088
1M	0.34 %	0.213 %	0.113	0.50 %**	0.228 %	0.029	0.34 %	0.214 %	0.118
2M	1.18 %***	0.302 %	< 0.001	1.62 %***	0.322 %	< 0.001	1.10 %***	0.303 %	< 0.001
3M	2.19 %***	0.370 %	< 0.001	2.84 %***	0.394 %	< 0.001	2.12 %***	0.371 %	< 0.001
6M	3.76 %***	0.522 %	< 0.001	4.75 %***	0.558 %	< 0.001	3.47 %***	0.525 %	< 0.001
n	2284			2284			2284		

	Small > Mid		
	t	**df**	**P-value**
1D***	202.02	4420	< 0.001
1M***	191.05	4418	< 0.001
2M***	184.70	4419	< 0.001
3M***	147.10	4420	< 0.001
6M***	130.52	4419	< 0.001

Small cap

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.37 %***	0.057 %	< 0.001	0.37 %***	0.058 %	< 0.001	0.38 %***	0.057 %	< 0.001
1M	1.67 %***	0.254 %	< 0.001	1.77 %***	0.259 %	< 0.001	1.77 %***	0.255 %	< 0.001
2M	2.99 %***	0.359 %	< 0.001	3.36 %***	0.366 %	< 0.001	2.86 %***	0.360 %	< 0.001
3M	3.96 %***	0.440 %	< 0.001	4.54 %***	0.449 %	< 0.001	3.59 %***	0.441 %	< 0.001
6M	5.99 %***	0.622 %	< 0.001	7.39 %***	0.634 %	< 0.001	5.29 %***	0.624 %	< 0.001
n	2275			2275			2275		

Hypothesis 2.2 – Growth vs value firms

First quartile - P/E ratio - Value companies

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.14 %***	0.049 %	0.005	0.15 %***	0.054 %	0.005	0.15 %***	0.049 %	0.002
1M	0.57 %***	0.218 %	0.009	0.31 %	0.243 %	0.198	0.66 %***	0.219 %	0.003
2M	1.65 %***	0.309 %	< 0.001	1.88 %***	0.344 %	< 0.001	1.49 %***	0.310 %	< 0.001
3M	2.70 %***	0.378 %	< 0.001	2.80 %***	0.422 %	< 0.001	2.31 %***	0.379 %	< 0.001
6M	3.62 %***	0.535 %	< 0.001	4.66 %***	0.596 %	< 0.001	2.97 %***	0.536 %	< 0.001
n	1556			1556			1556		

	Fourth (Growth) > First (Value)		
	t	**df**	**P-value**
1D***	61.29	2758	< 0.001
1M***	66.60	2759	< 0.001
2M***	16.37	2759	< 0.001
3M***	6.12	2759	< 0.001
6M***	31.37	2758	< 0.001

Second quartile - P/E ratio

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.11 %**	0.046 %	0.013	0.08 %	0.052 %	0.124	0.11 %**	0.046 %	0.017
1M	0.60 %***	0.204 %	0.003	0.39 %*	0.232 %	0.091	0.58 %***	0.204 %	0.005
2M	1.28 %***	0.289 %	< 0.001	1.87 %***	0.329 %	< 0.001	1.01 %***	0.289 %	< 0.001
3M	2.19 %***	0.354 %	< 0.001	2.88 %***	0.402 %	< 0.001	1.61 %***	0.354 %	< 0.001
6M	4.19 %***	0.500 %	< 0.001	5.17 %***	0.569 %	< 0.001	2.96 %***	0.501 %	< 0.001
n	1549			1549			1549		

Third quartile - P/E ratio

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.05 %	0.050 %	0.288	0.10 %*	0.055 %	0.065	0.06 %	0.050 %	0.195
1M	0.39 %*	0.223 %	0.082	0.39 %	0.248 %	0.112	0.41 %*	0.223 %	0.065
2M	0.67 %**	0.315 %	0.034	0.79 %**	0.351 %	0.024	0.76 %**	0.315 %	0.016
3M	1.02 %***	0.386 %	0.008	0.89 %**	0.430 %	0.039	1.16 %***	0.385 %	0.003
6M	2.67 %***	0.545 %	< 0.001	3.07 %***	0.607 %	< 0.001	2.60 %***	0.545 %	< 0.001
n	1554			1554			1554		

Fourth quartile - P/E ratio - Growth companies

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.27 %***	0.070 %	< 0.001	0.31 %***	0.074 %	< 0.001	0.30 %***	0.071 %	< 0.001
1M	1.22 %***	0.315 %	< 0.001	1.37 %***	0.332 %	< 0.001	1.29 %***	0.316 %	< 0.001
2M	1.88 %***	0.445 %	< 0.001	2.56 %***	0.469 %	< 0.001	1.87 %***	0.447 %	< 0.001
3M	2.80 %***	0.545 %	< 0.001	3.42 %***	0.574 %	< 0.001	2.81 %***	0.547 %	< 0.001
6M	4.37 %***	0.771 %	< 0.001	5.16 %***	0.812 %	< 0.001	4.51 %***	0.774 %	< 0.001
n	1550			1550			1550		

Hypothesis 2.3 – Firm Leverage

First quartile - D/E ratio - Low leverage

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.21 %***	0.069 %	0.003	0.2 %***	0.075 %	0.001	0.20 %***	0.069 %	0.004
1M	1.56 %***	0.307 %	< 0.001	1.7 %***	0.336 %	< 0.001	1.40 %***	0.307 %	< 0.001
2M	2.60 %***	0.434 %	< 0.001	3.3 %***	0.475 %	< 0.001	2.44 %***	0.434 %	< 0.001
3M	3.69 %***	0.531 %	< 0.001	4.2 %***	0.582 %	< 0.001	3.33 %***	0.531 %	< 0.001
6M	5.26 %***	0.751 %	< 0.001	5.9 %***	0.824 %	< 0.001	4.30 %***	0.751 %	< 0.001
n	957			957			957		

	Fourth (High leverage) > First (Low leverage)		
	t	**df**	**P-value**
1D	-65.22	1712	1.000
1M	-91.50	1713	1.000
2M	-96.06	1713	1.000
3M	-75.23	1714	1.000
6M	-43.95	1712	1.000

Second quartile - D/E ratio

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.04 %	0.059 %	0.541	0.03 %	0.070 %	0.693	0.05 %	0.059 %	0.421
1M	0.48 %*	0.262 %	0.069	0.02 %	0.314 %	0.951	0.61 %**	0.263 %	0.020
2M	0.35 %	0.371 %	0.347	0.63 %	0.443 %	0.157	0.73 %*	0.372 %	0.051
3M	0.63 %	0.455 %	0.168	0.23 %	0.543 %	0.674	1.15 %**	0.456 %	0.012
6M	3.13 %***	0.643 %	< 0.001	3.02 %***	0.768 %	< 0.001	3.77 %***	0.644 %	< 0.001
n	956			956			956		

Third quartile - D/E ratio

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	-0.02 %	0.058 %	0.700	0.00 %	0.069 %	0.962	0.01 %	0.059 %	0.914
1M	0.14 %	0.261 %	0.579	-0.11 %	0.310 %	0.718	0.26 %	0.265 %	0.336
2M	1.28 %***	0.369 %	< 0.001	1.45 %***	0.439 %	0.001	1.46 %***	0.375 %	< 0.001
3M	2.07 %***	0.452 %	< 0.001	2.00 %***	0.537 %	< 0.001	2.40 %***	0.459 %	< 0.001
6M	2.77 %***	0.639 %	< 0.001	2.02 %***	0.760 %	0.008	3.70 %***	0.650 %	< 0.001
n	912			912			912		

Fourth quartile - D/E ratio - High leverage

	Market MDL			**Constant Mean Return MDL**			**Multifactor MDL**		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.03 %	0.048 %	0.523	0.08 %	0.064 %	0.238	0.03 %	0.048 %	0.598
1M	0.45 %**	0.214 %	0.035	0.44 %	0.287 %	0.122	0.30 %	0.213 %	0.161
2M	0.95 %***	0.303 %	0.002	2.03 %***	0.405 %	< 0.001	0.46 %	0.302 %	0.126
3M	2.11 %***	0.371 %	< 0.001	3.13 %***	0.497 %	< 0.001	1.18 %***	0.369 %	< 0.001
6M	3.95 %***	0.524 %	< 0.001	6.14 %***	0.702 %	< 0.001	2.27 %***	0.523 %	< 0.001
N	934			934			934		

Hypothesis 2.4 – Firm Industry

Basic Materials

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.28 %*	0.166 %	0.087	0.36 %**	0.180 %	0.047	0.28 %*	0.167 %	0.092
1M	-0.35 %	0.741 %	0.633	-0.52 %	0.804 %	0.517	-0.57 %	0.745 %	0.446
2M	0.06 %	1.048 %	0.954	0.00 %	1.138 %	0.997	-0.49 %	1.054 %	0.641
3M	-0.30 %	1.284 %	0.813	-0.61 %	1.393 %	0.661	-0.67 %	1.291 %	0.603
6M	1.46 %	1.815 %	0.423	1.92 %	1.970 %	0.330	0.53 %	1.825 %	0.772
n	352			352			352		

Consumer Goods

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.12 %	0.092 %	0.198	0.19 %*	0.101 %	0.056	0.12 %	0.093 %	0.210
1M	0.41 %	0.411 %	0.314	0.10 %	0.450 %	0.825	0.23 %	0.414 %	0.575
2M	1.34 %**	0.581 %	0.021	1.24 %*	0.637 %	0.052	1.18 %**	0.586 %	0.045
3M	3.07 %***	0.712 %	< 0.001	2.63 %***	0.780 %	0.001	2.95 %***	0.718 %	< 0.001
6M	2.68 %***	1.007 %	0.008	1.92 %*	1.103 %	0.082	2.79 %***	1.015 %	0.006
n	651			651			651		

Consumer Services

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.00 %	0.079 %	0.992	-0.02 %	0.086 %	0.854	0.03 %	0.080 %	0.695
1M	0.80 %**	0.354 %	0.024	0.72 %*	0.384 %	0.062	1.12 %***	0.358 %	0.002
2M	1.20 %**	0.500 %	0.016	1.48 %***	0.544 %	0.007	1.26 %**	0.506 %	0.013
3M	1.79 %***	0.613 %	0.004	1.59 %**	0.666 %	0.017	1.74 %***	0.620 %	0.005
6M	5.39 %***	0.867 %	< 0.001	5.83 %***	0.942 %	< 0.001	5.17 %***	0.877 %	< 0.001
n	789			789			789		

Health Care

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.37 %***	0.137 %	0.007	0.35 %**	0.140 %	0.013	0.40 %**	0.139 %	0.005
1M	3.53 %***	0.615 %	< 0.001	3.67 %***	0.624 %	< 0.001	3.08 %***	0.621 %	< 0.001
2M	4.44 %***	0.870 %	< 0.001	4.98 %***	0.883 %	< 0.001	3.56 %***	0.878 %	< 0.001
3M	7.05 %***	1.065 %	< 0.001	7.63 %***	1.081 %	< 0.001	6.20 %***	1.075 %	< 0.001
6M	11.06 %***	1.507 %	< 0.001	12.37 %***	1.529 %	< 0.001	9.79 %***	1.520 %	< 0.001
n	556			556			556		

Financials

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.09 %**	0.037 %	0.011	0.10 %**	0.046 %	0.024	0.08 %**	0.037 %	0.039
1M	0.44 %***	0.165 %	0.008	0.38 %*	0.207 %	0.067	0.17 %	0.164 %	0.289
2M	0.67 %***	0.234 %	0.004	1.36 %***	0.292 %	< 0.001	0.25 %	0.232 %	0.282
3M	1.21 %***	0.286 %	< 0.001	1.66 %***	0.358 %	< 0.001	0.51 %*	0.284 %	0.075
6M	2.98 %***	0.405 %	< 0.001	3.55 %***	0.506 %	< 0.001	1.51 %***	0.402 %	< 0.001
n	1400			1400			1400		

Industrials

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.24 %***	0.052 %	< 0.001	0.28 %***	0.057 %	< 0.001	0.27 %***	0.052 %	< 0.001
1M	0.58 %**	0.234 %	0.013	0.50 %*	0.254 %	0.051	1.00 %***	0.234 %	< 0.001
2M	1.50 %***	0.330 %	< 0.001	1.88 %***	0.360 %	< 0.001	2.09 %***	0.331 %	< 0.001
3M	2.22 %***	0.405 %	< 0.001	2.63 %***	0.441 %	< 0.001	2.86 %***	0.405 %	< 0.001
6M	2.89 %***	0.573 %	< 0.001	3.87 %***	0.623 %	< 0.001	4.03 %***	0.573 %	< 0.001
n	1922			1922			1922		

Oil & Gas

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.96 %*	0.553 %	0.093	0.91 %	0.581 %	0.128	1.04 %*	0.547 %	0.067
1M	3.23 %	2.472 %	0.202	3.56 %	2.596 %	0.182	4.78 %*	2.445 %	0.061
2M	7.90 %**	3.496 %	0.032	7.25 %*	3.672 %	0.059	10.02 %***	3.458 %	0.007
3M	15.39 %***	4.282 %	0.001	13.87 %***	4.497 %	0.005	20.09 %***	4.235 %	< 0.001
6M	31.99 %***	6.055 %	< 0.001	31.08 %***	6.360 %	< 0.001	38.92 %***	5.989 %	< 0.001
n	28			28			28		

Technology

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.19 %**	0.086 %	0.030	0.12 %	0.089 %	0.164	0.20 %**	0.086 %	0.020
1M	1.69 %***	0.387 %	< 0.001	1.68 %***	0.398 %	< 0.001	1.53 %***	0.384 %	< 0.001
2M	3.64 %***	0.547 %	< 0.001	3.74 %***	0.564 %	< 0.001	3.08 %***	0.543 %	< 0.001
3M	4.36 %***	0.670 %	< 0.001	5.00 %***	0.690 %	< 0.001	3.18 %***	0.665 %	< 0.001
6M	6.39 %***	0.948 %	< 0.001	7.59 %***	0.976 %	< 0.001	3.87 %***	0.941 %	< 0.001
n	653			653			653		

Telecommunications

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	-0.02 %	0.107 %	0.865	-0.04 %	0.118 %	0.719	0.00 %	0.108 %	0.965
1M	1.48 %***	0.481 %	0.002	1.20 %**	0.527 %	0.023	1.52 %***	0.485 %	0.002
2M	2.13 %***	0.680 %	0.002	3.12 %***	0.746 %	< 0.001	2.19 %***	0.686 %	0.002
3M	1.87 %**	0.832 %	0.025	2.44 %***	0.913 %	0.008	1.87 %**	0.840 %	0.027
6M	1.45 %	1.177 %	0.218	3.01 %**	1.291 %	0.020	1.17 %	1.187 %	0.325
n	257			257			257		

Utilities

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	-0.05 %	0.460 %	0.913	0.00 %	0.488 %	0.997	-0.34 %	0.447 %	0.455
1M	0.08 %	2.061 %	0.970	-0.09 %	2.181 %	0.967	-1.37 %	1.998 %	0.501
2M	1.07 %	2.915 %	0.718	1.41 %	3.084 %	0.653	-1.78 %	2.826 %	0.536
3M	-2.06 %	3.570 %	0.571	-1.36 %	3.777 %	0.723	-6.67 %*	3.461 %	0.070
6M	4.17 %	5.048 %	0.419	7.86 %	5.341 %	0.158	-8.91 %*	4.895 %	0.085
n	19			19			19		

>		Consumer Goods			Consumer Services			Financials			Health care			Industrials			Oil & Gas			Technology			Telecommunications			Utilities		
		t	df	P-value	t	df	P-value	t	df	P-value	t	df	P-value	t	df	P-value	t	df	P-value	t	df	P-value	t	df	P-value	t	df	P-value
Basic Materials	1D	17.36	470	< 0.001	30.71	424	< 0.001	21.40	360	< 0.001	-8.57	646	1.000	4.95	364	< 0.001	-6.47	27	1.000	10.09	456	< 0.001	27.28	599	< 0.001	3.16	18	0.003
	1M	-18.01	471	1.000	-27.91	424	1.000	-19.88	360	1.000	-82.06	646	1.000	-23.53	364	1.000	-7.65	27	1.000	-48.37	457	1.000	-36.90	599	1.000	-0.91	18	0.813
	2M	-21.24	471	1.000	-19.50	424	1.000	-10.80	360	1.000	-65.44	646	1.000	-25.61	364	1.000	-11.82	27	1.000	-59.85	456	1.000	-29.53	599	1.000	-1.51	18	0.925
	3M	-45.62	470	1.000	-29.17	424	1.000	-21.93	360	1.000	-89.68	646	1.000	-36.60	364	1.000	-19.32	27	1.000	-63.69	456	1.000	-25.34	599	1.000	2.14	18	0.023
	6M	-11.66	470	1.000	-38.70	424	1.000	-15.61	360	1.000	-82.86	646	1.000	-14.65	364	1.000	-26.59	27	1.000	-47.65	456	1.000	0.04	599	0.484	-2.34	18	0.984
Consumer Goods	1D				26.06	1290	< 0.001	6.60	749	< 0.001	-37.42	942	1.000	-32.03	797	1.000	-8.07	27	1.000	-14.21	1297	1.000	17.98	412	< 0.001	1.60	18	0.063
	1M				-19.02	1289	1.000	-1.33	749	0.908	-101.65	942	1.000	-9.99	797	1.000	-6.03	27	1.000	-57.78	1297	1.000	-31.20	412	1.000	0.71	18	0.244
	2M				4.79	1289	< 0.001	28.56	749	< 0.001	-71.46	942	1.000	-6.75	797	1.000	-9.92	27	1.000	-73.52	1297	1.000	-16.40	412	1.000	0.41	18	0.345
	3M				36.02	1290	< 0.001	64.32	749	< 0.001	-74.98	942	1.000	28.71	797	< 0.001	-15.22	27	1.000	-33.84	1297	1.000	20.26	412	< 0.001	6.26	18	0.000
	6M				-54.13	1290	1.000	-7.35	749	1.000	-111.71	942	1.000	-5.09	797	1.000	-25.60	27	1.000	-68.67	1297	1.000	14.68	412	< 0.001	-1.29	18	0.894
Consumer Services	1D							-31.68	984	1.000	-58.01	813	1.000	-78.70	1081	1.000	-9.21	27	1.000	-43.01	1337	1.000	2.41	351	0.008	0.47	18	0.321
	1M							27.49	986	< 0.001	-94.18	813	1.000	16.03	1082	< 0.001	-5.20	27	1.000	-45.14	1336	1.000	-20.70	351	1.000	1.81	18	0.044
	2M							28.43	986	< 0.001	-79.02	812	1.000	-15.54	1081	1.000	-10.13	27	1.000	-87.54	1337	1.000	-20.17	351	1.000	1.87	18	0.039
	3M							25.29	985	< 0.001	-104.79	813	1.000	-18.22	1081	1.000	-16.80	27	1.000	-75.38	1337	1.000	-1.45	351	0.926	2.25	18	0.019
	6M							73.74	985	< 0.001	-80.02	813	1.000	74.62	1082	< 0.001	-23.24	27	1.000	-20.87	1337	1.000	49.41	351	< 0.001	4.69	18	0.000
Financials	1D										-47.54	587	1.000	-155.14	3317	< 0.001	-8.31	27	1.000	-26.91	765	1.000	16.56	267	< 0.001	1.37	18	0.094
	1M										-116.97	587	1.000	-21.29	3317	1.000	-5.99	27	1.000	-79.56	765	1.000	-34.31	267	1.000	0.75	18	0.230
	2M										-100.83	587	1.000	-85.51	3317	1.000	-10.95	27	1.000	-133.36	765	1.000	-34.16	267	1.000	-0.60	18	0.723
	3M										-127.51	587	1.000	-84.81	3317	1.000	-17.52	27	1.000	-115.57	765	1.000	-12.70	267	1.000	3.99	18	< 0.001
	6M										-124.81	587	1.000	5.26	3317	< 0.001	-25.36	27	1.000	-88.47	765	1.000	20.54	267	< 0.001	-1.03	18	0.842
Health Care	1D													22.67	602	< 0.001	-5.62	27	1.000	27.62	905	< 0.001	44.30	626	< 0.001	4.02	18	< 0.001
	1M													110.69	602	< 0.001	-18.01	27	1.000	60.92	905	< 0.001	51.69	625	< 0.001	7.29	18	< 0.001
	2M													77.99	602	< 0.001	-21.24	27	1.000	18.77	904	< 0.001	41.09	625	< 0.001	5.03	18	< 0.001
	3M													104.65	602	< 0.001	-45.62	27	1.000	51.42	904	< 0.001	75.20	625	< 0.001	11.11	18	< 0.001
	6M													125.39	602	< 0.001	-11.66	27	1.000	63.22	904	< 0.001	98.77	625	< 0.001	5.94	18	< 0.001
Industrials	1D																-6.91	27	1.000	14.30	819	< 0.001	38.00	272	< 0.001	2.75	18	0.007
	1M																-5.67	27	1.000	-68.99	819	1.000	-29.30	272	1.000	1.07	18	0.150
	2M																-9.68	27	1.000	-94.17	819	1.000	-14.57	272	1.000	0.65	18	0.263
	3M																-16.27	27	1.000	-76.97	820	1.000	6.65	272	< 0.001	5.23	18	0.000
	6M																-25.43	27	1.000	-89.20	820	1.000	19.24	272	< 0.001	-1.11	18	0.859
Oil & Gas	1D																			7.40	27	< 0.001	9.37	27	< 0.001	6.82	43	< 0.001
	1M																			3.30	27	0.001	3.75	27	< 0.001	4.74	43	< 0.001
	2M																			6.45	27	< 0.001	8.71	27	< 0.001	7.27	43	< 0.001
	3M																			13.62	27	< 0.001	16.67	27	< 0.001	15.16	43	< 0.001
	6M																			22.36	27	< 0.001	26.63	27	< 0.001	17.09	43	< 0.001
Technology	1D																						27.59	394	< 0.001	2.27	18	0.018
	1M																						6.44	393	< 0.001	3.41	18	0.002
	2M																						31.77	393	< 0.001	3.84	18	0.001
	3M																						42.81	393	< 0.001	7.84	18	< 0.001
	6M																						60.09	393	< 0.001	1.92	18	0.036
Telecom	1D																									0.31	18	0.381
	1M																									2.95	18	0.004
	2M																									1.58	18	0.065
	3M																									4.79	18	< 0.001
	6M																									-2.34	18	0.985

Hypothesis 2.5 – Firm Reporting

Adjacent to quarterly reports

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	σ	P-value	CAR-bar	σ	P-value	CAR-bar	σ	P-value
1D	0.12 %***	0.040 %	0.003	0.13 %***	0.044 %	0.003	0.14 %***	0.040 %	< 0.001
1M	0.85 %***	0.178 %	< 0.001	0.66 %***	0.197 %	0.001	0.96 %***	0.178 %	< 0.001
2M	1.41 %***	0.252 %	< 0.001	1.95 %***	0.279 %	< 0.001	1.50 %***	0.252 %	< 0.001
3M	2.08 %***	0.308 %	< 0.001	2.68 %***	0.342 %	< 0.001	2.00 %***	0.309 %	< 0.001
6M	3.84 %***	0.436 %	< 0.001	4.80 %***	0.484 %	< 0.001	3.44 %***	0.437 %	< 0.001
n	2881			2881			2881		

Not adjacent to quarterly reports

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	σ	P-value	CAR-bar	σ	P-value	CAR-bar	σ	P-value
1D	0.21 %***	0.038 %	< 0.001	0.22 %***	0.041 %	< 0.001	0.21 %***	0.038 %	< 0.001
1M	0.96 %***	0.171 %	< 0.001	0.95 %***	0.183 %	< 0.001	0.92 %***	0.172 %	< 0.001
2M	1.93 %***	0.242 %	< 0.001	2.17 %***	0.259 %	< 0.001	1.71 %***	0.243 %	< 0.001
3M	2.91 %***	0.297 %	< 0.001	2.91 %***	0.317 %	< 0.001	2.65 %***	0.298 %	< 0.001
6M	4.49 %***	0.420 %	< 0.001	5.00 %***	0.449 %	< 0.001	4.07 %***	0.422 %	< 0.001
n	2284			2284			2284		

	Not adjacent to quarterly reports > Adjacent		
	t	df	P-value
1D***	81.48	4970	< 0.001
1M***	23.61	4973	< 0.001
2M***	75.52	4972	< 0.001
3M***	98.79	4972	< 0.001
6M***	54.47	4975	< 0.001

Hypothesis 2.6 – Momentum

Momentum

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	σ	P-value	CAR-bar	σ	P-value	CAR-bar	σ	P-value
1D	0.23 %***	0.045 %	< 0.001	0.22 %***	0.047 %	< 0.001	0.24 %***	0.045 %	< 0.001
1M	1.16 %***	0.201 %	< 0.001	1.10 %***	0.210 %	< 0.001	1.14 %***	0.202 %	< 0.001
2M	2.50 %***	0.284 %	< 0.001	2.35 %***	0.297 %	< 0.001	2.12 %***	0.286 %	< 0.001
3M	3.64 %***	0.348 %	< 0.001	3.17 %***	0.364 %	< 0.001	2.93 %***	0.350 %	< 0.001
6M	6.66 %***	0.492 %	< 0.001	5.62 %***	0.514 %	< 0.001	5.04 %***	0.495 %	< 0.001
n	3313			3313			3313		

No momentum

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	σ	P-value	CAR-bar	σ	P-value	CAR-bar	σ	P-value
1D	0.11 %***	0.033 %	0.001	0.15 %***	0.038 %	< 0.001	0.12 %***	0.032 %	< 0.001
1M	0.67 %***	0.146 %	< 0.001	0.55 %***	0.168 %	0.001	0.74 %***	0.145 %	< 0.001
2M	0.91 %***	0.206 %	< 0.001	1.79 %***	0.238 %	< 0.001	1.13 %***	0.205 %	< 0.001
3M	1.46 %***	0.252 %	< 0.001	2.45 %***	0.291 %	< 0.001	1.81 %***	0.251 %	< 0.001
6M	1.76 %***	0.356 %	< 0.001	4.21 %***	0.412 %	< 0.001	2.55 %***	0.355 %	< 0.001
n	3314			3314			3314		

	Momentum > No momentum		
	t	df	P-value
1D***	122.23	6037	< 0.001
1M***	114.65	6041	< 0.001
2M***	261.62	6039	< 0.001
3M***	291.79	6040	< 0.001
6M***	464.76	6038	< 0.001

Hypothesis 3.1 – Insider Position

Alternate and/or subsidiary board member

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.03 %	0.237 %	0.903	0.09 %	0.248 %	0.715	0.05 %	0.238 %	0.846
1M	2.89 %***	1.058 %	0.007	3.50 %***	1.107 %	0.002	2.65 %**	1.066 %	0.014
2M	5.29 %***	1.497 %	< 0.001	6.38 %***	1.565 %	< 0.001	2.62 %*	1.508 %	0.084
3M	6.47 %***	1.833 %	< 0.001	7.56 %***	1.917 %	< 0.001	2.53 %	1.847 %	0.173
6M	9.63 %***	2.592 %	< 0.001	11.08 %***	2.711 %	< 0.001	4.23 %	2.612 %	0.108
n	148			148			148		

Managing Director

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.39 %***	0.090 %	< 0.001	0.38 %***	0.096 %	< 0.001	0.39 %***	0.090 %	< 0.001
1M	1.89 %***	0.401 %	< 0.001	1.81 %***	0.431 %	< 0.001	2.02 %***	0.402 %	< 0.001
2M	4.07 %***	0.567 %	< 0.001	4.15 %***	0.609 %	< 0.001	4.02 %***	0.568 %	< 0.001
3M	6.27 %***	0.695 %	< 0.001	6.25 %***	0.746 %	< 0.001	6.04 %***	0.695 %	< 0.001
6M	10.86 %***	0.982 %	< 0.001	11.57 %***	1.055 %	< 0.001	9.92 %***	0.984 %	< 0.001
n	662			662			662		

Board member parent firm

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.20 %***	0.056 %	< 0.001	0.24 %***	0.059 %	< 0.001	0.22 %***	0.056 %	< 0.001
1M	0.94 %***	0.250 %	< 0.001	0.95 %***	0.265 %	< 0.001	1.04 %***	0.251 %	< 0.001
2M	1.75 %***	0.354 %	< 0.001	2.05 %***	0.375 %	< 0.001	1.93 %***	0.355 %	< 0.001
3M	2.27 %***	0.432 %	< 0.001	2.76 %***	0.459 %	< 0.001	2.49 %***	0.435 %	< 0.001
6M	4.69 %***	0.612 %	< 0.001	5.52 %***	0.650 %	< 0.001	4.71 %***	0.615 %	< 0.001
n	2008			2008			2008		

Other executive

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.00 %	0.084 %	0.994	-0.01 %	0.094 %	0.914	0.07 %	0.085 %	0.443
1M	0.55 %	0.374 %	0.146	0.42 %	0.420 %	0.317	0.73 %*	0.379 %	0.055
2M	0.44 %	0.530 %	0.405	0.54 %	0.594 %	0.365	0.61 %	0.536 %	0.259
3M	0.88 %	0.649 %	0.177	1.27 %*	0.728 %	0.082	1.14 %*	0.657 %	0.084
6M	2.35 %**	0.918 %	0.011	3.13 %***	1.029 %	0.003	2.36 %**	0.929 %	0.011
n	475			475			475		

Large shareholder

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.11 %	0.084 %	0.175	0.20 %**	0.089 %	0.028	0.12 %	0.084 %	0.159
1M	-0.98 %***	0.375 %	0.009	-0.35 %	0.397 %	0.376	-1.12 %***	0.375 %	0.003
2M	-0.74 %	0.531 %	0.164	0.35 %	0.561 %	0.533	-1.26 %**	0.530 %	0.018
3M	-0.10 %	0.651 %	0.873	1.27 %*	0.688 %	0.065	-1.13 %*	0.650 %	0.082
6M	-3.84 %***	0.920 %	< 0.001	-1.00 %	0.973 %	0.303	-5.01 %***	0.919 %	< 0.001
n	798			798			798		

Other position

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.13 %***	0.040 %	< 0.001	0.12 %**	0.045 %	0.011	0.14 %***	0.040 %	0.001
1M	1.16 %***	0.180 %	< 0.001	0.74 %***	0.203 %	< 0.001	1.14 %***	0.180 %	< 0.001
2M	1.85 %***	0.255 %	< 0.001	2.13 %***	0.287 %	< 0.001	1.80 %***	0.255 %	< 0.001
3M	2.79 %***	0.312 %	< 0.001	2.54 %***	0.351 %	< 0.001	2.72 %***	0.312 %	< 0.001
6M	4.76 %***	0.440 %	< 0.001	4.63 %***	0.497 %	< 0.001	4.60 %***	0.442 %	< 0.001
n	2504			2504			2504		

		Board member parent firm			*Large shareholder*			*Managing Director*			*Other Executive*			*Other Position*		
>		**t**	**df**	**P-value**	**t**	**df**	**P-value**	**t**	**df**	**P-value**	**t**	**df**	**P-value**	**t**	**df**	**P-value**
Alternate/ subsidiary board member	1D	-8.98	148	1.000	-4.34	154	1.000	-18.12	157	1.000	1.48	159	0.070	-5.36	148	1.000
	1M	22.32	148	< 0.001	43.99	154	< 0.001	11.36	157	< 0.001	26.44	159	< 0.001	19.85	148	< 0.001
	2M	28.72	148	< 0.001	48.42	154	< 0.001	9.74	157	< 0.001	38.63	159	< 0.001	27.89	148	< 0.001
	3M	27.79	148	< 0.001	43.12	154	< 0.001	1.29	157	0.100	36.41	159	< 0.001	24.40	148	< 0.001
	6M	23.13	148	< 0.001	62.50	154	< 0.001	-5.67	157	1.000	33.51	159	< 0.001	22.82	148	< 0.001
Board member parent firm	1D				27.79	1088	< 0.001	-49.48	836	1.000	50.62	578	< 0.001	47.63	3535	< 0.001
	1M				133.56	1089	< 0.001	-56.90	836	1.000	22.06	578	< 0.001	-32.85	3535	1.000
	2M				121.94	1089	< 0.001	-99.17	837	1.000	51.03	577	< 0.001	-11.24	3533	1.000
	3M				95.14	1088	< 0.001	-139.42	836	1.000	44.60	577	< 0.001	-45.00	3536	1.000
	6M				241.57	1089	< 0.001	-152.05	837	1.000	52.88	578	< 0.001	-4.47	3530	1.000
Large shareholder	1D							-59.53	1371	1.000	23.63	999	< 0.001	-6.15	916	1.000
	1M							-139.94	1370	1.000	-70.33	999	1.000	-155.63	916	1.000
	2M							-165.95	1370	1.000	-38.43	998	1.000	-133.07	916	1.000
	3M							-179.57	1371	1.000	-26.07	999	1.000	-121.21	916	1.000
	6M							-292.89	1371	1.000	-116.35	999	1.000	-255.05	916	1.000
Managing Director	1D										74.72	1060	< 0.001	70.96	733	< 0.001
	1M										57.80	1061	< 0.001	45.27	733	< 0.001
	2M										110.49	1060	< 0.001	97.97	733	< 0.001
	3M										134.20	1060	< 0.001	125.61	733	< 0.001
	6M										149.67	1060	< 0.001	155.51	733	< 0.001
Other Executive	1D													-34.08	516	< 0.001
	1M													-35.12	516	1.000
	2M													-56.75	516	1.000
	3M													-62.88	516	1.000
	6M													-56.11	516	1.000

Hypothesis 3.2 – Trade Volume, absolute

First quartile absolute volume - Small absolute volume

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.17 %***	0.064 %	0.008	0.17 %**	0.067 %	0.010	0.20 %***	0.064 %	0.002
1M	1.30 %***	0.285 %	< 0.001	1.17 %***	0.299 %	< 0.001	1.29 %***	0.286 %	< 0.001
2M	2.51 %***	0.402 %	< 0.001	2.86 %***	0.423 %	< 0.001	1.98 %***	0.405 %	< 0.001
3M	3.44 %***	0.494 %	< 0.001	3.66 %***	0.518 %	< 0.001	2.81 %***	0.496 %	< 0.001
6M	5.51 %***	0.698 %	< 0.001	6.15 %***	0.732 %	< 0.001	4.42 %***	0.701 %	< 0.001
n	1622			1622			1622		

	Small absolute > Large absolute		
	t	**df**	**P-value**
1D***	30.58	3195	< 0.001
1M***	172.28	3195	< 0.001
2M***	159.84	3198	< 0.001
3M***	131.55	3194	< 0.001
6M***	124.61	3196	< 0.001

Second quartile absolute volume

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.22 %***	0.056 %	< 0.001	0.24 %***	0.061 %	< 0.001	0.24 %***	0.057 %	< 0.001
1M	1.27 %***	0.253 %	< 0.001	0.99 %***	0.274 %	< 0.001	1.39 %***	0.253 %	< 0.001
2M	2.09 %***	0.358 %	< 0.001	2.18 %***	0.387 %	< 0.001	2.44 %***	0.358 %	< 0.001
3M	3.11 %***	0.437 %	< 0.001	2.81 %***	0.474 %	< 0.001	3.42 %***	0.439 %	< 0.001
6M	4.13 %***	0.619 %	< 0.001	3.94 %***	0.671 %	< 0.001	4.92 %***	0.621 %	< 0.001
n	1621			1621			1621		

Third quartile absolute volume

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.17 %***	0.051 %	< 0.001	0.18 %***	0.057 %	0.001	0.17 %***	0.051 %	0.001
1M	0.90 %***	0.227 %	< 0.001	0.50 %*	0.255 %	0.051	0.92 %***	0.227 %	< 0.001
2M	1.11 %***	0.321 %	< 0.001	1.28 %***	0.360 %	< 0.001	1.18 %***	0.322 %	< 0.001
3M	1.70 %***	0.392 %	< 0.001	1.62 %***	0.441 %	< 0.001	1.65 %***	0.394 %	< 0.001
6M	3.60 %***	0.556 %	< 0.001	3.80 %***	0.624 %	< 0.001	3.47 %***	0.557 %	< 0.001
n	1621			1621			1621		

Fourth quartile absolute volume - Large absolute volume

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.11 %**	0.052 %	0.041	0.11 %*	0.057 %	0.056	0.09 %*	0.052 %	0.070
1M	0.28 %	0.231 %	0.227	0.67 %***	0.256 %	0.009	0.23 %	0.232 %	0.312
2M	1.20 %***	0.327 %	< 0.001	2.02 %***	0.362 %	< 0.001	0.93 %***	0.327 %	0.005
3M	2.12 %***	0.400 %	< 0.001	3.23 %***	0.443 %	< 0.001	1.74 %***	0.401 %	< 0.001
6M	3.76 %***	0.567 %	< 0.001	5.75 %***	0.626 %	< 0.001	2.55 %***	0.567 %	< 0.001
n	1646			1646			1646		

Hypothesis 3.3 – Trade Volume, relative

First quartile relative volume - Small relative volume

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.26 %***	0.057 %	< 0.001	0.28 %***	0.061 %	< 0.001	0.27 %***	0.058 %	< 0.001
1M	0.33 %	0.257 %	0.193	0.51 %*	0.273 %	0.060	0.56 %**	0.257 %	0.031
2M	1.04 %***	0.363 %	0.004	1.51 %***	0.386 %	< 0.001	1.27 %***	0.364 %	0.001
3M	1.56 %***	0.445 %	< 0.001	2.01 %***	0.472 %	< 0.001	1.63 %***	0.446 %	< 0.001
6M	2.07 %***	0.629 %	0.001	3.31 %***	0.668 %	< 0.001	2.08 %***	0.630 %	0.001
n	1648			1648			1648		

	Large relative > Small relative		
	t	**df**	**P-value**
1D	-10.19	3278	1.000
1M***	129.76	3278	< 0.001
2M***	122.54	3279	< 0.001
3M***	122.47	3279	< 0.001
6M***	163.35	3279	< 0.001

Second quartile relative volume

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.06 %	0.053 %	0.298	0.12 %**	0.058 %	0.048	0.08 %	0.053 %	0.135
1M	0.34 %	0.238 %	0.152	0.45 %*	0.261 %	0.087	0.35 %	0.239 %	0.140
2M	0.91 %***	0.338 %	0.007	1.43 %***	0.369 %	< 0.001	0.77 %**	0.338 %	0.022
3M	1.64 %***	0.414 %	< 0.001	2.14 %***	0.452 %	< 0.001	1.49 %***	0.414 %	< 0.001
6M	2.87 %***	0.584 %	< 0.001	3.93 %***	0.639 %	< 0.001	2.53 %***	0.585 %	< 0.001
n	1652			1652			1652		

Third quartile relative volume

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.13 %**	0.054 %	0.015	0.11 %*	0.060 %	0.077	0.15 %***	0.055 %	0.007
1M	1.48 %***	0.243 %	< 0.001	1.16 %***	0.267 %	< 0.001	1.46 %***	0.245 %	< 0.001
2M	2.28 %***	0.344 %	< 0.001	2.64 %***	0.378 %	< 0.001	2.06 %***	0.346 %	< 0.001
3M	3.55 %***	0.421 %	< 0.001	3.74 %***	0.463 %	< 0.001	3.08 %***	0.424 %	< 0.001
6M	6.17 %***	0.594 %	< 0.001	6.92 %***	0.655 %	< 0.001	5.24 %***	0.599 %	< 0.001
n	1640			1640			1640		

Fourth quartile relative volume - Large relative volume

	Market MDL			Constant Mean Return MDL			Multifactor MDL		
	CAR-bar	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**	**CAR-bar**	**σ**	**P-value**
1D	0.24 %***	0.058 %	< 0.001	0.24 %***	0.062 %	< 0.001	0.23 %***	0.058 %	< 0.001
1M	1.50 %***	0.257 %	< 0.001	1.17 %***	0.278 %	< 0.001	1.38 %***	0.257 %	< 0.001
2M	2.60 %***	0.363 %	< 0.001	2.73 %***	0.394 %	< 0.001	2.40 %***	0.364 %	< 0.001
3M	3.46 %***	0.446 %	< 0.001	3.34 %***	0.482 %	< 0.001	3.30 %***	0.446 %	< 0.001
6M	5.65 %***	0.630 %	< 0.001	5.42 %***	0.682 %	< 0.001	5.33 %***	0.630 %	< 0.001
n	1646			1646			1646		