Stockholm School of Economics

Master's Thesis in Finance

Why do insiders trade?

- A study on what motivates insiders to trade

Abstract

This thesis is based on insider transaction data from September 2000 to December 2008 on the Stockholm Stock Exchange. The study gives further insight into insider trading explanations by investigating the connection between insider trades and stock returns in two main methods; one on the individual insider trade level and one on the aggregate insider trade level. On the individual trade level, we find a significant relationship between past return and insider trades both on single trade and when the trades are made in clusters, but no significant relationship with future returns. On the individual trade level with trades made by CEOs only, we find a positive relationship between future return and insider trading volume on 6 months, but no significant relationship to past returns, indicating that CEOs trade on other information than other insiders. On the aggregate stock level, we find in line with Seyhun (1988) that aggregate insider trades predict future abnormal returns of the market.

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1 Introduction

1.1 Background

Nobel Prize- winning economist and Columbia University professor Joseph Stiglitz, says that economists are to blame for the financial crisis of 08/09, which exposed “major flaws” in the prevailing ideas. Among the flawed premises is the assumption that investors are on average rational, and that financial markets are competitive and efficient. Further, the housing bubble which ended up igniting the crisis was fuelled by the idea that prices would go up forever, according to Stiglitz (Bloomberg, Jan 2nd 2010). Still, the current general finance theories leave little room for investor sentiment and other behavioural biases.

Research has found evidence of that insider trades are generally followed by abnormal returns. Studies by Summers and Sweeney (1998) and Seyhun (1998) show that insider traders both generate an abnormal return, and that outside investors can gain from mimicking their transactions. On the Swedish market, Wahlström (2003) shows that insider trades generate abnormal returns but that following this strategy does not, due to transaction costs.

In this study, we will test the relationship between insider trading and stock returns and try to deduce what drives insider trading. We test if insider trading affects sentiment at the individual stock level, or if it is sentiment that affects insider trading. If the trade is a positive signal to the market the event of an insider trade should be followed by a positive abnormal return rather than preceded by a negative one.

1.2 Purpose

The purpose of this research is to better understand insider trading. By investigating the dynamics of insider trades we hope to gain some insight into how they are connected to sentiment . Our method is an attempt to distinguish between market sentiment and insider information during insider trades. By comparing the abnormal stock return before and after the insider trades (see more under 3 Hypotheses), we hope to gain some new insights into why an insider trades.

1.3 Contribution

There are numerous research on insider trading, the regulation, and whether insiders achieve abnormal return on their investments. What this thesis tries to do is to build upon the work of Seyhun, who tries to explore *why* insiders trade. The main contribution is that the thesis explores the reasons for insider trading, in particular trying to build a bridge between insider trading and investor sentiment.

1.4 Limitations

The thesis is limited to the Swedish market. Similarities in regulation and other market mechanisms determine the extension to which the results can be used in other markets. The regressions use insider data from 2000-09-01 to 2008-12-31, which limits the tests to this period. As the rest of the market, the trading pattern by insiders has evolved both due to shifting regulation and the ability of the market regulators to enforce them. When it comes to the investigated period, the market has been turbulent both in the early part with the dotcom-bubble and in the latter part, with the recent financial crisis. Therefore, the results of the tests should be seen in the limelight of this, and the limitations it brings.

2 Theoretical Framework and Previous Research

This thesis will focus on the connection between sentiment and insider trading. To understand this, the following section will cover the thesis' theoretical framework, focusing on the concepts of insider trading and investor sentiment separately. This is to give the reader a background understanding before moving on to the previous research, which more focuses on the connection between these two concepts as it has been portrayed in earlier studies. The section ends with the theoretical framework and previous research for the extended analysis we make on our regressions: cluster transactions and insiders' role in the company.

2.1 Insider trading

Insiders are those who through their position in a company are considered to have access to privileged information. These include, among others, members of the board, executives and large shareholders (see 2.1.4 Insider Definition for further details).

There can be several reasons for why insiders trade (see 2.1.2 Insider Trading Explanations). However, it is important to distinguish between legal and illegal insider trading. According to Swedish regulation, it is illegal for an insider to trade stock or other financial instruments of the company in question, if the insider possesses information that is not known to the public that can affect the price of the security (Law 2005:377). An insider must report and register the transaction to the Swedish Financial Supervisory Authority (Finansinspektionen) within five days from the transaction date.

Previous research has found several examples of insiders generating abnormal returns and insider trading predicting market return (for example Seyhun, 1988, and Seyhun, 1992). These findings stand in contradiction to the Efficient Market Hypothesis (see 2.1.1 Insider trading and the EMH).

2.1.1 Insider trading and the EMH

The theoretical explanation for abnormal returns are usually that they are the result of specific risks in the market, that the model used to calculate the abnormal return does not take into account. Insider abnormal return is an example of one that has not been explained by a specific risk, but has generally been explained by the market driving the prices from their fundamental values.

In this context, insider trading is often put in contrast to the efficient market hypothesis, EMH, primarily developed by Fama (1970). The EMH presents three types of market efficiency: strong, semi-strong and weak form of market efficiency. In short, weak form of efficiency is that the market price only reflects historical information about the share price. This means that historical prices cannot be used to predict future market prices (technical analysis). The semi-strong form of efficiency is when new information quickly is reflected in the share prices. That is, neither technical analysis nor fundamental analysis can be used to gain abnormal return. The strong form is when the market prices reflect all available information, both public and private; only genuinely new information can change the price of the share.

Shleifer (2000) states three arguments for the EMH. (i) market participants are rational and can value securities correctly; (ii) even if there are irrational investors, these are uncorrelated and hence cancel themselves out; (iii) if irrational investors are correlated, the existence of rational arbitrageurs will revert market prices to their fundamental values. However, Shleifer (2000) creates a model that, assuming that rational arbitrageurs are risk averse, the risk associated with this trading is too large to drive the prices to their fundamental values. The strong surge in the field of behavioural finance is another sign that the EMH is not the almighty truth.

Nonetheless, the EMH has been the central proposition of finance since introduced by Fama (1970), and it is therefore an important aspect of this field. The implication of this is that no insider information can be used to gain abnormal return. Most research is focused on this aspect of insider trading, i.e. whether insiders gain on their insider trades. This would indicate that the market is not efficient in the strong form.

2.1.2 Insider Trading Explanations

Focusing on the legal insider trading, research has still somewhat differencing explanations on why insiders trade and why they achieve abnormal return on their investments. The following section will explore some of these explanations.

Incentive alignment. According to corporate finance theory, a CEO or another stakeholder in a company will create more value if his or her incentives are aligned with the company's interests. Jensen and Murphy (1990) found a positive relationship between stock performance and performance-pay incentives for the top management. In US, a large part of the performance incentives consists of stock ownership and options.

Sign of low sentiment. In Baker and Wurgler (2007), insider trading is considered a sign of low sentiment in the market. This is also an implication of Seyhun (1988); the conclusion is that insiders are able to identify when the market sentiment is low by realizing that their own stock is undervalued (see further under 2.3.2 Seyhun).

Signalling effect. Because of its position, the insider is better at interpreting the information that the market has. Therefore, a buy or a sell by an insider should be considered a signal that affects the stock price towards a level where all investors have access to the same information and knowledge (Nogeman and Li, 2008, and Sjöholm and Skoog, 2006). Previous research shows that the significant effect because of this information will happen within one trading week. (Nogeman and Li, 2008). It should be noted that only the buy trades are supposed to be a clear-cut signal for investors. A sell could have other reasons than that the stock is overvalued; such as need of money or tax purposes.

2.1.3 Cluster Transactions

Sjöholm and Skoog (2006) introduce the concept of cluster transactions. If two or more insiders do the same type of trade within a short period of time, they argue that it is more likely that insiders are in fact trying to use inside information to their advantage. Sjöholm and Skoog (2006) find that abnormal returns indeed have been larger for cluster transactions. The explanation given is that the probability of insiders buying or selling stocks in their own firm for other reasons than maximizing their returns are in the case of cluster transaction very minor. And even if the probability of one insider selling his or her shares to free money for other purposes than this could be non-negligible, the probability that two or more insiders would simultaneously act in this manner is indeed negligible. Sjöholm and Skoog (2006) also conclude that cluster selling provides greater potential to generate abnormal return for investors than cluster buying. However, no explanation for this anomaly is given.

Cluster transactions are defined by Sjöholm and Skoog (2006) as follows:

1. A minimum of two individuals with an insider position in the company must have traded the stock
2. The trades have to be done within one trading week
3. All transactions must be of the same type, that is, they can either be all buy transactions or all sell transactions

2.1.4 Insider Definition

In his research, Seyhun uses US definition of insider trades; the open market volume of sales and purchases made by officers, directors, and large shareholders in their own firms. In previous research on the Swedish market (such as Sjöholm and Skoog, 2006, and Nogeman and Li, 2008) , which uses The Swedish Financial Supervisory Authority data, the insiders are defined in line with Swedish reporting regulations *Act concerning Reporting Obligations for Certain Holdings of Financial Instruments (2000:1087).* According to FI, an insider is a person who through his or her position in the company is considered to very likely have access to insider information about the company. The following persons are considered to have insider positions:

1. A member of the company's or the parent company's board
2. A managing director of the company or the parent company
3. An auditor of the company or the parent company
4. A partner in a partnership company that is the company's parent company, though not a limited partner
5. A holder of a senior executive post or a qualified function of a permanent nature at the company or the parent company, if the post or function normally have access to non-public information that can 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 normally have access to non-public information which can affect the company's share price
7. Larger shareholders who themselves, together with one or more natural or legal persons own at least ten per cent of the share capital or number of votes in the company

There are also regulations for people considered to be close related to the insider, where spouses or children also must report ownership and transactions, under certain conditions.

The definitions of insiders are hence similar in the US and Swedish research. Some differences lies in that Swedish regulation also reports auditors and persons with a close relationship in some cases. Research is scarce on the connection between type of insider and the return on insiders trade. In a study in the US OTC market, insiders close to the operations of the firm such as chairmen of the board, directors, officer-directors, and officers are found to trade on more valuable information than large, unaffiliated shareholders (Lin and Howe, 1990).

2.2 Sentiment

The history of the stock market is full of events that seem to imply investor sentiment as a major pricing factor. Research has therefore tried to understand this phenomenon. The theory is based on two assumptions:

(i) Investors are subject to sentiment (Delong, Shleifer, Summers, and Waldmann, 1990). Here investor sentiment is broadly defined as beliefs about cash flows and investment risks that are not justified solely by the facts at hand.

(ii) Betting against investors subject to sentiment is risky and costly. Therefore, the possibility of arbitrage is limited for rational investors to drive the prices to their fundamental value (Shleifer, 2000)

There is no doubt that investor sentiment is an important factor for the market as a whole:

> *"... the question is no longer, as it was a few decades ago, whether investor sentiment affects stock prices, but rather how to measure investor sentiment and quantify its effects" (Baker and Wurgler, 2007)*

One way to explain how individual investors under- or overreact to past returns or fundamentals is the "bottom up" approach, in which biases in individual investor psychology, such as overconfidence, representativeness and conservatism is used. Overall these models make predictions about patters in investor sentiment, stock prices and volume in a market wide perspective.

In Baker and Wurgler (2007), another approach is used which is "top down" and macroeconomic. This approach focuses on the measurement of reduced form, aggregate sentiment and traces its effect to market returns and individual stocks. This they argue, builds on broader assumptions of behavioural finance to explain no only that the level of stock prices in aggregate depends on sentiment, but also which stocks are most likely to be affected by sentiment.

2.2.1 Sentiment and the EMH

As discussed in 2.1.1 Insider trading and the EMH, the theory defines three types of market efficiency: weak form, semi-strong form and strong form. The sentiment theory stands in direct contradiction to these efficiencies; the traders are affected by other beliefs than solely the facts at hand.

2.3 Sentiment Explanations for Insider Trading

Insider trades are usually studied in terms of if and how much abnormal returns the insiders can achieve, and if the legislation is sufficient. However, the reason for the abnormal returns are not that thoroughly explored. Two main field specializations have connected insider trading with sentiment; Baker and Wurgler (2006 and 2007) have explored sentiment with help of insider trading, and Seyhun(1988 and 1992) has explored insider trading with a sentiment view.

2.3.1 Baker and Wurgler

Baker and Wurgler (2007) try to measure aggregate sentiment and relate its effect to market returns and individual stocks. In the sentiment proxy, Baker and Wurgler (2007) use a number imperfect measures, such as trading volume, dividend premium, and number and first day return on IPOs (Baker and Wurgler, 2007, p15).

Another factor that can be used, according to the authors, is insider trading. If insiders buy a lot in aggregate, an explanation is be that they know that the stocks are undervalued, which in turn could be due to negative sentiment. If the sentiment in the market is low, insiders with better knowledge about true fundamental values will buy shares, and therefore a high volume of insider buy trades can be tested as a proxy for low investor sentiment. Due to lack of data, investor trading is not used in the sentiment index, but tested over a 20 year time period toward this index. Insiders buying shares has a significant negative correlation with the sentiment index, and also with the underlying components of it (Baker and Wurgler, 2006).

2.3.2 Seyhun

Seyhun (1988) and Seyhun (1992) are important works about the connection between insider trading and market sentiment. The former focuses on the information content of aggregate insider trading and finds a positive relationship between this and future stock market returns; the latter tries to explain this relationship using the competing “fads” and “cash flow” hypotheses.

The Information Content of Aggregate Insider Trading

Previous studies on insider trading by among others Lorraine and Niederhoffer (1968), Jaffee (1974), Finnerty (1976) and Seyhun (1986) find that insiders identify and trade on mispricing in their own firm. Seyhun (1988) uses insider trading data from the period January 1975 to October 1981, finding a positive correlation between aggregate insider trading and future stock return. By analysing if insider trades can predict returns of the market as a whole, or if it predicts the return of the insider's specific firm, a separation is made on the type of information that the insider trade on. It is concluded that insiders' aggregate trading predicts the return of the market portfolio during the following two months. The conclusion is that the insiders identify when their own firm is mispriced; they then respond to these economy-wide economic factors as if they were firm-specific, and trade in their own shares.

More specific, net aggregate insider trading in a given month is positively correlated with the return of the market portfolio during the subsequent two months. In aggregate, insiders increase their stock purchases prior to a market increase, and increase aggregate sales prior to a stock market decline (Seyhun, 1988). These results are tested on the definition of aggregate insider trading such as the net dollar volume traded, aggregate net portion of firm traded, and found to be not sensitive to this.

The Fads and Cash Flow Hypotheses

Seyhun (1992) investigates the reason for the positive relationship between insider trading and future returns by testing two competing explanations; movement of share price away from its fundamental value (fads hypothesis), and changes in business conditions (cash flow hypothesis). These two hypotheses build on the assumption that insiders can identify mispricing in its own firm, which could be due to market conditions, either sentiment or fundamental ones.

The cash flow hypothesis states that insiders can predict future cash flows before the market, so that insiders' trades are correlated with future corporate cash flows. To the extent that these future cash flows are related to the economic activity of the market as a whole, the insiders' can also predict the market in terms of measures such as Index of Industrial Production and Gross National Product; variables associated with business conditions and fundamental values (Seyhun, 1992).

The fads hypothesis instead builds on that stock prices can deviate away from fundamental values due to sentiment. The insiders are expected to realise that their own firm is mispriced, and buy stock. If insiders buy a lot in aggregate during a period of time, this mispricing is market wide and insider trading on aggregate will predict market return (Seyhun, 1992). But, on the other hand, if the mispricing is firm specific, these trades will cancel each other out, and insider trading on aggregate will not predict market return.

Apart from finding a strong relationship between past aggregate insider trading and future excess stock return, Seyhun (1992) also finds evidence that aggregate insider trading is positively related to future real activity measured as growth rates of corporate profits, Index of Industrial Production and the Gross National Product. However, all of the relation between insider trading and future market return cannot be explained by future real activity. After including other explanatory variables such as past stock returns, dividend yields, and default spreads, aggregate insider trading captures a component of stock returns not related to these or future real activity. This implies that both changes in business conditions and movements away from fundamentals (sentiment) contribute to this information content of insider trading. Insider trading signals can also be used to predict negative future excess stock return, as the fads hypothesis states.

3 Hypotheses

This thesis tries to build on Seyhun (1992) in that it explores another way of separating reasons for insider trading. The following assumptions are made regarding insider trading:

(i) Insiders buy when they believe their stock will generate excess return

(ii) Future excess return can stem from the stock being undervalued due to negative sentiment, or it could stem from future real activity or future positive sentiment

(iii) Current negative sentiment, future real activity, and future positive sentiment are uncorrelated

By investigating the relationship between stock performance before and after an insider trade, some insights into what drives insider trades and sentiment can be gained.

If an insider buys shares because he or she believes that the stock is undervalued due to low sentiment, then sentiment is what drives insider trading. For this to be true, we expect to see on average insiders buying stocks with poor past performance.

That is, if sentiment is what drives insider trading, then stocks with the highest buy (sell) volume of insider trading are stocks with particularly low (high) past performance, since stocks with low (high) past performance proxies for low (high) sentiment among investors.

Hypothesis 1. Stocks with high buy (sell) volume of insider trading are stock with low (high) past performance.

On the other hand, if insider trading is because the insider expects future real activity or future high sentiment in the market, we expect no relationship between the volume of insider trading and past performance, but a positive correlation between the sign of insider trading and future performance for the individual stock.

Aggregate insider trading

To benchmark against previous research on the connection between insider trading and sentiment, we also look at aggregate trading and its correlation with the market return. If sentiment is defined as something affecting the market as a whole, insiders aggregate trading should predict the performance of the market as a whole, as Seyhun (1988) finds.

Hypothesis 2. Aggregate insider trading is positively correlated to stock market excess return.

4 Methodology

4.1 Methodology Overview

To test the connection between the return of the stock and insider trades, we use pooled cross-sectional time series regressions. This method combines the information content of the time intervals as well as the information of the cross-sectional data. By combining these two data properties we end up with 10 657 observations post-drop.

To test our hypotheses, we have divided the tests into 4 basic regressions, which will be discussed further under header 4.1.1 Basic Regressions. The subsequent chapters will explain and develop these regressions further. To separate these regressions from the other equations in this thesis, we have numbered them 1-4, instead of naming them with letters.

4.1.1 Basic Regressions

The first part will test hypothesis 1 by running the Basic Regressions (1) and (2) on the individual stock level.

$$Traded\ volume = a + \ b \cdot past\ abnormal\ return \tag{1}$$

$$Traded\ volume = a + \ b \cdot future\ abnormal\ return \tag{2}$$

In the following sections, these Basic Regressions will be discussed. Section 4.2 Basic Regressions (1) and (2) will develop regressions (1) and (2) further.

To benchmark to the Seyhun (1988) and (1992) tests, we will also test the information content of aggregate insider trading. This will be done mainly by running the Basic Regressions (3) and (4). The Basic Regression (3) builds on the Seyhun (1988) and (1992) logic; that insiders recognise when their own stock is undervalued because of market conditions and in aggregate generate excess returns on these investments.

$$Future\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading \tag{3}$$

Basic Regression (4) builds on the same logic, but extends the test to why the insiders trade. If the reason is that the stock is undervalued due to past bad performance, we expect to see a negative relationship between aggregate insider trading and past excess market return (see 3 Hypotheses).

$$Past\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading \qquad (4)$$

4.2 Basic Regressions (1) and (2)

4.2.1 Pooled Cross-Sectional Time Series Regressions

A pooled cross-sectional time series regression uses time series data pooled from events during a certain time period. Each event is defined as an insider transaction; the date when the insider believes that the stocks will under- or over perform and hence decide to buy or sell the stock. Data points gathered for each of these transactions are the 1-year backward looking sector beta, and future and past abnormal returns.

No satisfactory guidelines are given on the time period for calculating returns (Seyhun 1988); the solution to this is to use several different time periods. To enable comparisons with previous research we have chosen to use similar time periods as Seyhun (1992), which covers most time periods used in the other theses referred to here. Furthermore, we have decided to use 2 years of return estimate, to catch a possible long-term effect. Hence, time periods chosen are 1 month, 3 months, 6 months, 1 year and 2 years.

4.2.2 Past and Future Abnormal Return

We will use the market model suggested by MacKinlay et al (1997), which relates the return of a given security to the return of the market portfolio. To account for differences in expected return for different sectors, we use the sector definitions as given by the Global Industry Classification Standard (GICS). GICS defines a sector for each share, and for each sector an index is reported.

The one factor market model suggested by MacKinlay et al (1997) has the following form:

$$R_{i,t} = \alpha_i + \beta_i \cdot R_{s,t} + \varepsilon_{i,t} \qquad \text{(a)}$$

$R_{i,t}$ is the return of security *i* at time *t*, $R_{s,t}$ is the return of the sector portfolio, approximated by the GICS sector indices, at time *t*, and $\varepsilon_{i,t}$ is the error term of the model, with a mean of zero. α_i and β_i are the security-specific parameters that are estimated in regressions using the estimation window for normal return one year before the event date. The beta is interpreted as a sensitivity of the security return to the sector index, and can also be interpreted as a measure of risk. We have calculated betas for each transaction using the model above, with 1 year of daily data of sector returns and stock returns.

Returns are calculated on adjusted prices, that is, prices adjusted for events such as stock splits and dividends. The abnormal return is the realized return subtracted by the return we would expect giving a certain condition X at time t. In this case, this translates into the return given that the share trades in a certain sector. The return of the security is $E(R_{i,t}|X_t)$, and the abnormal return AR for share i at time t becomes:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}|X_t) \qquad \text{(b)}$$

A common method is to use log when calculating returns. This is convenient since multiplicative returns, used for calculating cumulative returns, then become additive. The abnormal return of each share is thus calculated by subtracting the log of the sector return times the 1-year beta from the log of the adjusted prices normal return.

4.2.3 Traded Volume

In Basic Regressions (1) and (2), the factor *Traded volume* is used. This is defined as the value of the shares traded, i.e. the number of shares traded multiplied by the unadjusted price per share on the transaction date. A positive sign indicates a buy and a negative sign indicates a sale of shares.

An alternative is to use a measurement of the traded volume relative to the total market capitalisation in order to account for different sizes of companies. Our measure is better in the way that we capture the trade in relation to the insider trader. A buy is related to his or her fortune, and not related to the company in question. Furthermore, previous research has found little differences between different definitions of insider trading measurements (see 2.1 Insider trading).

4.3 Basic Regressions (3) and (4), Aggregate Insider Trading

In addition to the methods introduced in 4.2 Basic Regressions (1) and (2), Basic Regressions (3) and (4) also use the factor aggregate insider trading. For each month t, the Net number of Insider trades, NI, in the market has been added according to (c). H is the type of trade; a buy transaction has the value 1 and a sell transaction has the value -1. Hence, in this calculation the size of the transaction does not affect the factor aggregate insider trading. J_t denotes the number of insider transactions in month *t* for all companies in the sample. NI_t is the variable *aggregate insider trading* in the Basic Regressions (3) and (4)

$$NI_t = \sum_{j=1}^{J_t} H_j \qquad \text{(c)}$$

4.4 Extensions to the Basic Regressions

In line with the previous research and theory, some alterations can be done do further analyse insider trading data. We have chosen to investigate cluster trades, suggested by Sjöholm and Skoog (2006), type of insider, somewhat explored by Lin and Howe (1990), and industry sector, discussed by Seyhun (1992).

4.4.1 Cluster trades

The concept of cluster trades was introduced in 2.1.3 Cluster Transactions. To facilitate a comparison of the results, we have defined clusters in the same way as Sjöholm and Skoog (2006), that is:

1. A minimum of two different insiders must have traded the stock
2. The transactions must have taken place within one trading week
3. All transactions within the trading week must be of the same sign

The concept has been used in the Basic Regressions (1) and (2) in the following way. For each cluster that has been identified according to the criteria's in Sjöholm and Skoog (2006). The traded volume, cluster is calculated as traded volume multiplied by the unadjusted prices for each transaction in the cluster. Equations (1a) and (2a) shows the cluster insider trades regressions.

$$Traded\ volume, cluster = a + \ b \cdot past\ abnormal\ return, cluster \tag{1a}$$

$$Traded\ volume, cluster = a + \ \ b \cdot future\ abnormal\ return, cluster \tag{2a}$$

To ensure full comparison, we defined the event date to be the date of the last transaction in the cluster series. This might reduce the size of the abnormal returns as the market may have started to adjust the price of the security already. The implication of this is that setting the event date as the last transaction date should not generate a larger abnormal return than what is actually true. In this way we do not exaggerate the returns and this alternative gives as pure results as possible regarding measuring the combined effect of the transactions.

The cluster concept can also be used in the Basic Regressions (3) and (4). The method straightforward; instead of aggregating insider trades in each time period, we have aggregated clusters, see equation (d) and regressions (3a) and (4a) below. Further to the variables described in 4.2 Basic Regressions (1) and (2), we here use NIC, Net number of Insider Cluster. A buy cluster is, as the individual trade, the value 1, and a sell cluster gives C the value -1. NIC_t is the variable *aggregate insider trading* in the regressions (3a) and (4a).

$$NIC_t = \sum_{j=1}^{J_t} C_j \tag{d}$$

$$Future\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading\ clusters \tag{3a}$$

$$Past\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading\ clusters \tag{4a}$$

4.4.2 CEO Transactions

In line with Lin and Howe (1990) (see 2.1.4 Insider Definition), it can be assumed that the CEO knows more about the company than a large shareholder since he or she is in charge of the day-to-day operations of the company. To evaluate this, the Basic Regressions (1) and (2) are altered into (1b) and (2b), only using insider transactions when the CEO is the insider who trades (see below).

$$Traded\ volume,\ CEO = a + b \cdot past\ abnormal\ return, CEO \tag{1b}$$

$$Traded\ volume, CEO = a + b \cdot future\ abnormal\ return, CEO \tag{2b}$$

The above role-of-insider adjustment can also be used in Basic Regressions (3) and (4). In the aggregate formula, we have here only used transactions made by CEOs, see equation (e) and regressions (3b) and (4b). We here use NICEO, Net number of Insider trades by a CEO. A buy gives D the value 1, and a sell -1. $NICEO_t$ is the variable *aggregate insider trading, CEO* in the regressions (3b) and (4b).

$$NICEO_t = \sum_{j=1}^{J_t} D_j \tag{e}$$

$$Future\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading, CEO \tag{3b}$$

$$Past\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading, CEO \tag{4b}$$

CEO definition

The CEO is here defined as the CEO of the company in question, regardless of what other roles the he or she has in the company. Positions such as the CEO of the parent company are not included.

5 Data

5.1 Data Sources

The data used is based on two sources; insider transaction data sourced from the Swedish Financial Supervisory Authority (FI, Finansinspektionen), and market data sourced from Thomson Datastream.

FI publishes insider transactions of companies noted on the Stockholm Exchange on their website, www.fi.se, for the last 10 years. We have chosen to look at insider transactions for the period 2000-09-01 to 2009-12-31. The insider transaction data gives us the number of shares traded, and these transactions are matched with help of the ISIN-code to the unadjusted share price to calculate the total transaction volume.

5.2 Dropped observations

The total number of transactions published by FI for the period 2000-09-01 – 2009-12-31 are 109 462. A summary of the transactions used in the thesis is shown in Table 1.

Buy	
Number of transactions	34 339
Average size of transaction	6 543 539
Max transaction	9 455 000 000
Standard deviation of transactions	61 910 861
Sell	
Number of transactions	18 760
Average size of transaction	4 278 024
Max transaction	2 885 274 329
Standard deviation of transactions	51 133 416
Total sample	
Number of transactions	109 462
Average size of transaction (a)	14 935 208
Max transaction (a)	116 501 000 000
Standard deviation of transactions (a)	562 453 340

Table 1. Descriptive statistics for total FI sample. Transaction sizes are given in SEK.
(a): Calculated using absolute numbers

Table 2 shows drop criteria and the number of observations dropped associated with each criterion. In the matching of insider transactions and return using the ISIN number, some transactions cannot be matched. The amount of transactions dropped due to missing data is 30 944.

The data from FI includes many types of transactions, including buy and sell transactions, option exercises and share issues. In this thesis, we have only used regular buy and sell of company stock, i.e. only shares named A-series, B-series, etc. The purpose of this exclusion of trades is that we want to look at the "regular trades", without influences of other market events such as capital operations. It is not possible to control for all types of events, but the amount is smaller this way. When it comes to stock options and more complex financial instruments the reasons for the transaction are also often more complex. Stock options can be part of incentives schemes and rights issues are often complex in their nature. For the purpose of investigating investor market sentiment, only the pure stock transactions are suitable. The number of transactions dropped associated with this criterion is 30 236.

A special type of insider transactions are those made by listed companies. These trades are often large and not the typical transaction that we want to investigate. The number of transactions in the sample carried out by listed companies and hence dropped is 9 179.

A number of transactions are of the same amount of shares but of opposite signs, made by one insider during a short period of time. Reason for this can be tax regulations, and these observations are therefore dropped. The criterion for this drop is that the trades with opposite signs are made within 5 days of each other, and it results in a drop of 9 054 observations.

In line with Sjöholm and Skoog (2006), we have filtered our transactions for smaller trades, here defined as trades with a total value of less than SEK 50 000. Trades with lower values can be interpreted as being done with other motives than the "ordinary trade", and these transactions are hence dropped. By dropping smaller transactions, we are left with those with the largest signalling power (Sjöholm and Skoog, 2006). The number of trades defined as "small" according to this criterion is 60 732.

A final set of dropped observations are those that are commented on in the data from FI. The reason for this is to exclude as many special transactions as possible. The number of transactions with comments is 6 166.

Dropped observations	
Total sample	88 800
Missing data	30 944
Other transactions	56 363
Other instruments	30 236
Listed companies	9 179
Opposite sign transactions	9 054
Small transactions	60 732
Commented transactions	6 166

Table 2. Dropped observations. The drop criteria are not mutually exclusive

Table 3 below shows the same descriptive statistics as Table 1 post drop. A more detailed description of the dataset follows in section 5.3 Data Description.

Buy	
Number of transactions	6 850
Average size of transaction	4 905 611
Max transaction	1 954 279 037
Standard deviation of transactions	39 453 561
Sell	
Number of transactions	3 807
Average size of transaction	8 404 599
Max transaction	2 180 146 103
Standard deviation of transactions	61 885 736
Total sample	
Number of transactions	10 657
Average size of transaction (a)	6 155 555
Max transaction (a)	2 180 146 103
Standard deviation of transactions (a)	48 694 853

Table 3. Descriptive Statistics of Sample Post Drop. Transaction sizes are given in SEK.
(a): Calculated using absolute numbers

As seen above the dataset was shrunk to 10 657 observations. This is because in addition to the 88 800 observations dropped for the above stated reasons, 10 005 observations were dropped because of lack of return data. We can observe that the ratio of buy and sell transactions is similar post drop to same ratio pre drop. This indicates that the drop criteria affected buy and sell transactions in more or less the same way. The size of the remaining transactions is smaller and this is mainly due to that transactions made by listed companies were removed. These transactions were among the largest in the original dataset.

5.3 Data Description

5.3.1 Buy and Sell Transactions

Table 4 shows an analysis of the buy and sell transactions for the years in the sample. The analysed time period contains both bull and bear markets which can be seen in the data.

Year	2000*	2001	2002	2003	2004	2005	2006	2007	2008
Buy Transactions									
Number of transactions	176	297	628	628	559	636	823	1 517	1 586
Average size of transaction	10 393 569	602 985	3 030 809	2 805 247	4 216 660	5 845 646	9 493 603	4 475 923	4 572 437
Median transaction size	304 050	185 000	404 425	401 000	273 700	284 000	357 000	469 200	352 800
Max transaction size	437 536 000	11 745 000	61 047 000	88 500 000	217 600 000	334 400 000	1 954 279 037	551 075 000	1 605 000 000
Standard deviation of transactions	48 114 262	1 279 733	8 183 573	6 783 019	17 412 432	23 519 550	80 898 961	23 386 122	46 457 841
Sell Transactions									
Number of transactions	101	252	334	424	481	560	624	634	397
Average size of transaction	13 855 385	1 797 212	4 455 244	3 008 480	5 586 421	8 925 823	8 953 485	7 074 907	24 237 718
Median transaction size	665 350	265 650	400 750	599 090	476 100	632 769	627 000	692 500	423 000
Max transaction size	440 440 000	77 490 000	138 750 000	138 960 000	384 000 000	399 000 000	2 180 146 103	420 750 000	1 605 000 000
Standard deviation of transactions	53 878 163	5 883 277	14 587 885	11 521 656	24 093 605	33 724 705	97 085 509	27 475 976	130 554 325
All Transactions									
Number of transactions	277	549	962	1 052	1 040	1 196	1 447	2 151	1 983
Average size of transaction (a)	11 655 820	1 151 155	3 525 364	2 887 158	4 850 174	7 287 869	9 260 684	5 241 965	8 509 460
Median transaction size (a)	449 500	223 200	403 750	471 000	341 625	397 000	466 000	532 500	372 000
Max transaction size (a)	440 440 000	77 490 000	138 750 000	138 960 000	384 000 000	399 000 000	2 180 146 103	551 075 000	1 605 000 000
Standard deviation of transactions (a)	50 223 291	4 134 385	10 857 974	8 993 652	20 772 092	28 780 945	88 212 405	24 684 117	72 065 329

Table 4. Buy and Sell analysis through time. Transaction sizes are given in SEK.
* only includes data from September onwards. (a): Calculated using absolute numbers

Worth mentioning is the evident increase in number of trades starting in 2006 and culminating in 2008 with almost 2000 transactions during the year, almost 400 % more than in 2001. Also, it is interesting to see that the average transaction size for sell transactions in 2008 increased dramatically to 24 million SEK. However, the average transaction size for buy transactions remains fairly unchanged. The medians of the transactions are significantly smaller than the averages indicating that most transactions are fairly small. The medians are also much more stable over time, this shows that most of the volatility lies in the largest transactions made. The buy and sell analysis through time table tells us that our dataset reflects the events that has dominated both the global and the Swedish market during the past decade.

5.3.2 Cluster Transactions

Table 5 shows a description of the data as defined by the cluster definition in 2.1.3 Cluster Transactions. Table 6 shows the same data over time.

Buy	
Number of transactions	764
Average size of transaction	13 834 135
Max transaction	735 000 000
Standard deviation of transactions	46 410 654
Sell	
Number of transactions	333
Average size of transaction	19 226 575
Max transaction	768 000 000
Standard deviation of transactions	61 375 301
Total sample	
Number of transactions	1 097
Average size of transaction (a)	15 471 038
Max transaction (a)	768 000 000
Standard deviation of transactions (a)	51 446 473

Table 5. Descriptive statistics of cluster transactions. Transaction sizes are given in SEK.
(a): Calculated using absolute numbers

Year	2000*	2001	2002	2003	2004	2005	2006	2007	2008
Number of clusters									
Buy	23	40	95	102	102	125	147	250	213
Sell	8	17	19	39	48	54	60	61	27
All	31	57	114	141	150	179	207	311	240
Number of transactions in cluster									
Average	3	3	4	4	3	3	3	4	4
Max	8	16	20	36	11	13	14	24	31
Standard deviation	1	3	3	4	2	2	2	3	3
Size of cluster									
Average	39 039 065	4 761 269	20 058 069	10 640 771	15 036 291	28 758 268	10 893 312	14 894 213	11 451 403
Max	565 000 000	44 400 000	279 000 000	96 000 000	309 000 000	768 000 000	281 000 000	372 000 000	353 000 000
Standard deviation	120 206 667	9 638 080	51 244 428	17 853 451	41 953 448	102 680 505	33 561 879	34 028 952	38 357 447
Size of individual transactions in cluster									
Average	12 307 170	12 307 170	12 307 170	12 307 170	12 307 170	12 307 170	12 307 170	12 307 170	12 307 170
Max	141 300 000	141 300 000	141 300 000	141 300 000	141 300 000	141 300 000	141 300 000	141 300 000	141 300 000
Standard deviation	35 128 897	35 128 897	35 128 897	35 128 897	35 128 897	35 128 897	35 128 897	35 128 897	35 128 897

Table 6. Cluster transactions through time. Transaction sizes are given in SEK.
* only includes data from September onwards

The number of clusters increases steadily over the time period, following the pattern of the individual trades both on the buy and sell side. Also worth mentioning is the high number of clusters compared to the number of trades. For example, in 2008 we have 1 586 buy transactions, and 213 buy clusters. This could be due to the fact that insiders are prohibited from buying during certain time periods, for example prior to the release of the annual report.

5.3.3 CEO Transactions

Table 7 below shows descriptive statistics on transactions made by the CEO of the company. Table 8 shows the same data through time.

Buy	
Number of transactions	786
Average size of transaction	2 393 004
Max transaction	368 388 000
Standard deviation of transactions	15 106 910
Sell	
Number of transactions	307
Average size of transaction	5 826 367
Max transaction	177 500 000
Standard deviation of transactions	18 099 207
Total sample	
Number of transactions	1 093
Average size of transaction (a)	3 338 234
Max transaction (a)	368 388 000
Standard deviation of transactions (a)	16 051 285

Table 7. Descriptive statistics on CEO transactions. Transaction sizes are given in SEK.
(a): Calculated using absolute numbers

Year	2000*	2001	2002	2003	2004	2005	2006	2007	2008
Buy Transactions									
Number of transactions	10	35	54	89	93	86	107	176	136
Average size of transaction	38 134 293	1 266 441	1 449 517	1 306 247	3 036 674	1 689 362	3 438 660	1 676 962	2 505 662
Median transaction size	902 650	492 900	250 200	297 500	222 800	366 000	584 000	526 750	345 125
Max transaction size	368 388 000	11 745 000	16 000 000	27 902 800	124 974 000	18 598 140	115 726 549	55 425 000	77 466 609
Standard deviation of transactions	116 046 043	2 250 888	3 120 502	3 960 062	14 569 739	3 023 449	12 900 656	5 607 224	9 515 480
Sell Transactions									
Number of transactions	2	14	29	54	65	43	46	29	25
Average size of transaction	89 037 550	9 071 336	6 061 155	7 452 268	4 926 307	2 881 620	6 483 819	6 371 231	8 247 401
Median transaction size	89 037 550	2 092 500	520 000	1 264 278	608 000	1 317 735	3 172 000	1 462 500	925 000
Max transaction size	177 500 000	77 490 000	138 750 000	138 960 000	92 363 895	14 952 960	53 420 950	49 011 840	82 830 821
Standard deviation of transactions	125 104 797	20 097 450	25 602 103	23 818 318	14 048 424	3 544 766	10 569 945	11 888 245	17 505 443
All Transactions									
Number of transactions	12	49	83	143	158	129	153	205	161
Average size of transaction (a)	46 618 169	3 496 411	3 060 812	3 627 122	3 814 055	2 086 781	4 354 198	2 341 030	3 397 237
Median transaction size (a)	902 650	981 000	333 000	377 000	330 750	609 500	915 250	542 500	383 750
Max transaction size (a)	368 388 000	77 490 000	138 750 000	138 960 000	124 974 000	18 598 140	115 726 549	55 425 000	82 830 821
Standard deviation of transactions (a)	113 285 615	11 210 321	15 329 886	15 178 998	14 342 723	3 242 178	12 292 256	7 004 223	11 256 740

Table 8. CEO transactions through time. Transaction sizes are given in SEK.
* only includes data from September onwards, (a): Calculated using absolute numbers

The CEO data shows the same pattern as the overall data. Out of the total sample, the CEO transactions are about 10 % of the number of transactions, and about 6 % of the total value in absolute terms. In the through-time analysis, the CEO part of the total transactions tend to be higher in the years 2002 – 2006.

6 Results

6.1 The Basic Regressions (1) and (2)

The Basic Regressions (1) and (2) were introduced in4.2 Basic Regressions (1) and (2), the reader is reminded of the formulas below.

$$Traded\ volume = a + \ b \cdot past\ abnormal\ return \qquad (1)$$

$$Traded\ volume = a + \ \ b \cdot future\ abnormal\ return \qquad (2)$$

Table 9 below shows the results of the regressions for the “past” and “future” time periods 1 month, 3 months, 6 months, 1 year and 2 years. The “Past” column corresponds to the b’s in the Basic Regression (1), the “Future” column corresponds to the b’s in the Basic Regression (2). T-statistics are given in the parentheses below, and the stars indicate any significance level. The regression shows no correlation between future excess market return and insider trading: The 3 months time period shows the highest t-statics, although none of the significance levels are met. Basic Regression (2) on the other hand shows significant results on the 6 months and 1 year time period on the 5 % level. It should also be noted that the coefficients in the right column are all positive, while they are all negative in the left column.

The negative coefficient in Basic Regression (2) indicates that a negative past market excess return is associated with insiders buying shares in the company. The positive coefficient in the right hand side column (Basic Regression (1)) should be interpreted as, on average, future positive return is associated with insiders buying shares. The latter is not statistically significant though.

Excess return on insider trading volume		
	Past	Future
1 month	-3897321.4 (-1.08)	5355835.0 (1.27)
3 months	-4132288.2 (-1.87)	3438098.0 (1.48)
6 months	-3184186.9* (-2.11)	1769975.8 (1.12)
1 year	-2367634.1* (-2.27)	417482.8 (0.39)
2 years	-1243751.2 (-1.78)	885959.0 (1.17)
t statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001		

Table 9. Results from the Basic Regressions (1) and (2).

6.2 Aggregate Insider Trading, Basic Regression (3) and (4)

Seyhun (1988 and 1992) find that the insiders profit are mainly due to insiders' ability to understand when their own share is undervalued due to market conditions. If the excess return of the market is positively correlated with aggregate insider trading, it means that the insiders trade based on information concerning the whole market. Recall the Basic regressions (3) and (4):

$$Future\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading \qquad (3)$$

$$Past\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading \qquad (4)$$

In line with Seyhun's research, the time periods tested here are 1 month, 3 months, 6 months and 1 year.

The results from Basic Regression (3) are shown in Table 10 and the results from Basic Regression (4) are shown in Table 11 below.

6.2.1 Aggregate Insider Trading and Future Excess Market Return

In line with the findings of Seyhun (1988 and 1992), we find a positive correlation between the aggregate net number of insider trades and the future excess market return. This correlation is strongest for longer time periods of aggregate number of trades, as well as the for the longer time periods of future return. For example, 1 year of aggregate return can predict also the 1 month excess market return, although with less significance. Conversely, even 1 month of aggregate insider trading can predict the 1 year market excess return. However, longer time periods of aggregate net number of insider trades can predict the market return also for shorter time periods. The significant results form a triangular pattern, see Table 10 below. N is the number of observations in each regression.

Aggregate past net number of insider trades	Future excess market return			
	1 month	3 months	6 months	1 year
1 month	-0.0000756 (-0.27)	0.000165 (0.31)	0.00134 (1.50)	0.00553*** (3.89)
3 months	0.0000247 (0.22)	0.000271 (1.29)	0.000984** (2.82)	0.00314*** (6.00)
6 months	0.0000608 (1.03)	0.000283* (2.58)	0.000778*** (4.36)	0.00203*** (7.89)
1 year	0.0000762* (2.39)	0.000270*** (4.80)	0.000611*** (6.94)	0.00120*** (8.95)
N	100	100	100	100

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 10. Results from Basic Regression (3)

6.2.2 Aggregate Insider Trading and Past Excess Market Return

The basic regression (4) yields the results shown in Table 11 below. Overall, the past excess market returns for long periods (1 year and 6 months) correlate with the aggregate net number of insider trades short-term (1 month to 6 months) negatively. The negative sign of the correlation should be interpreted as that a negative past excess return in the market is correlated with insiders buying in aggregate. Apparently, only longer time periods of negative excess market return is associated with insiders buying a lot, where the buying occurs during a shorter time period.

Aggregate past net number of insider trades	Past excess market return			
	1 month	3 months	6 months	1 year
1 month	-0.000266 (-0.97)	-0.000898 (-1.74)	-0.00202* (-2.32)	-0.00381** (-3.00)
3 months	-0.0000767 (-0.70)	-0.000334 (-1.61)	-0.000840* (-2.41)	-0.00176*** (-3.49)
6 months	-0.00000333 (-0.06)	-0.0000724 (-0.64)	-0.000303 (-1.60)	-0.000791** (-2.88)
1 year	0.0000515 (1.60)	0.000114 (1.87)	0.000107 (1.01)	-0.000103 (-0.65)
N	100	100	100	100

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 11. Results from Basic Regression (4)

6.3 Alterations to Basic Regressions (1) and (2)

6.3.1 Cluster Transactions

Table 12 below shows the result of regressions (1a) and (2a), using the cluster method defined in 4.4.1 Cluster trades.

$$Traded\ volume, cluster = a + \ b \cdot past\ abnormal\ return, cluster \tag{1a}$$

$$Traded\ volume, cluster = a + \ \ b \cdot future\ abnormal\ return, cluster \tag{2a}$$

The results have a similar pattern as Table 9, with a negative correlation between past excess return of the share and insider trading (regression 1a). This regression yields more significant results than the results of the Basic Regression (1), showing also significant values in the 3 months period. The negative coefficient suggests that a period of negative excess return of the share (3 months to 1 year) is correlated with insiders buying in clusters.

In all time periods, there a positive coefficient on the regression of excess future return and insider trading (regression 2a), although the results are not significant. Compared with the Basic Regression (2), the cluster definitions yields higher t-statistics.

Excess return on insider trading volume (Cluster)		
	Past	**Future**
1 month	-23230209.0 (-1.84)	23477814.6 (1.59)
3 months	-24751852.5** (-3.16)	14184464.8 (1.66)
6 months	-19066493.8*** (-3.60)	7927581.1 (1.45)
1 year	-8163464.4* (-2.34)	2218257.0 (0.61)
2 years	-4026851.3 (-1.53)	2292560.1 (0.71)
t statistics in parentheses * p<0.05, ** p<0.01, *** p<0.001		

Table 12. Results of Regressions (1a) and (2a), cluster alteration.

6.3.2 CEO Transactions

Table 13 below shows the results of the regressions (1b) and (2b), introduced and described in 4.4.2 CEO Transactions.

$$Traded\ volume,\ CEO = a + \ b \cdot past\ abnormal\ return, CEO \qquad (1b)$$

$$Traded\ volume, CEO = a + \ \ b \cdot future\ abnormal\ return, CEO \qquad (2b)$$

Similarly to the results from the Basic Regressions (1) and (2), and the cluster alteration (1a) and (2a), the coefficients on the past excess returns are negative, while the coefficients on the future excess return are positive. However, here we have a different pattern in terms of significance and t-statistics. In both the Basic Regressions (1) and (2) and the cluster alterations (1a) and (2a), the left hand side columns show a pattern of having higher absolute values of the t-statistics. In the CEO regressions (1b) and (2b), it is the future column that has the higher t-statistics and also showing a p-value of 5 % for the 6 months period.

Regarding time periods, we see that mid- to long-term periods show higher t-statistics for the future excess return, while the only time period showing some value of t-statistic worth mentioning is the 2 years of negative excess return of the stock.

Excess return on insider trading volume (CEO)		
	Past	**Future**
1 month	-895419.1 (-0.22)	6874744.4 (1.31)
3 months	-373772.5 (-0.15)	3732668.7 (1.73)
6 months	-1079652 (-0.60)	3219669.9* (2.03)
1 year	-1255581.7 (-1.02)	2314968.3 (1.95)
2 years	-820793.2 (-1.26)	1004092.5 (1.73)

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 13. Results from regressions (1b) and (2b)

6.4 Alterations to the Basic Regressions (3) and (4)

6.4.1 Cluster Transactions

The results of the regressions (3a) and (4a) are summarised in Table 14 and Table 15 respectively.

$$Future\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading\ clusters \quad (3a)$$

$$Past\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading\ clusters \quad (4a)$$

Aggregate past net number of insider trade clusters	Future excess market return			
	1 month	3 months	6 months	1 year
1 month	-0.000654 (-0.34)	-0.00216 (-0.59)	0.00307 (0.49)	0.0290** (2.82)
3 months	-0.0004 (-0.50)	-0.0000135 (-0.01)	0.00312 (1.20)	0.0186*** (4.64)
6 months	0.000122 (0.28)	0.000883 (1.09)	0.00365** (2.70)	0.0129*** (6.53)
1 year	0.000406 (1.74)	0.00158*** (3.76)	0.00391*** (5.88)	0.00886*** (9.35)
N	100	100	100	100

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 14. Results of regression (3a), aggregate insider trading and future excess market return with cluster alteration.

Aggregate past net number of insider trade clusters	Past excess market return			
	1 month	3 months	6 months	1 year
1 month	-0.00154 (-0.81)	-0.00593 (-1.64)	-0.0142* (-2.34)	-0.0293** (-3.33)
3 months	-0.001 (-1.27)	-0.00331* (-2.22)	-0.00701** (-2.81)	-0.0145*** (-4.06)
6 months	-0.000332 (-0.78)	-0.0013 (-1.61)	-0.00318* (-2.36)	-0.00692*** (-3.57)
1 year	0.000193 (0.83)	0.000279 (0.62)	-0.000196 (-0.26)	-0.00207 (-1.85)
N	100	100	100	100

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 15. Results of regression (4a), aggregate insider trading and past excess market return with cluster alteration.

The results are similar to the results of the Basic Regressions (3) and (4), but differ somewhat when regarding significance levels. Generally, the results of regression (3a), Table 14, are less significant or showing a lower absolute number of the t-statistics. The opposite goes for Table 15, where the results of regressions (4a) are somewhat more significant than its Basic Regression (4) counterparts. When it comes to patterns regarding time periods and significance levels, the results are quite similar.

6.4.2 CEO Transactions

The results of regressions (3b) and (4b) are summarised in Table 16 and Table 17, respectively.

$$Future\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading, CEO \qquad (3b)$$

$$Past\ excess\ market\ return = a + b \cdot aggregate\ insider\ trading, CEO \qquad (4b)$$

Aggregate past net number of insider trades by CEOs	Future excess market return			
	1 month	3 months	6 months	1 year
1 month	-0.00116	0.00131	0.00617	0.0166
	(-0.56)	(0.33)	(0.92)	(1.47)
3 months	0.000304	0.00225	0.00614	0.0148**
	(0.30)	(1.16)	(1.86)	(2.70)
6 months	0.000583	0.00239	0.00523*	0.0141***
	(0.91)	(1.98)	(2.56)	(4.31)
1 year	0.000489	0.00192*	0.00473***	0.0117***
	(1.23)	(2.61)	(3.88)	(6.28)
N	100	100	100	100

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 16. Results of regression (3b), aggregate insider trade and future excess market return with CEO alteration.

Aggregate past net number of insider trades by CEOs	Past excess market return			
	1 month	3 months	6 months	1 year
1 month	-0.00511*	-0.0114**	-0.0190**	-0.0273**
	(-2.58)	(-3.04)	(-2.97)	(-2.86)
3 months	-0.00136	-0.00559**	-0.0122***	-0.0180***
	(-1.34)	(-3.00)	(-3.96)	(-3.93)
6 months	-0.000196	-0.00157	-0.00622**	-0.0111***
	(-0.31)	(-1.30)	(-3.13)	(-3.86)
1 year	0.000265	0.000536	-0.000402	-0.0032
	(0.67)	(0.71)	(-0.31)	(-1.69)
N	100	100	100	100

t statistics in parentheses
* p<0.05, ** p<0.01, *** p<0.001

Table 17. Results of regression (4b), aggregate insider trades and past excess market return with CEO alteration.

Compared to the results of the Basic Regressions (3) and (4), the results of (3b) and (4b) are similar. For the future return regressions, the results are generally less significant in regression (3b) than in Basic Regression (3). The triangle appearing Table 10 is now smaller, only time periods from 3 months and up are significant for the market excess returns and the aggregate net number of transactions.

7 Analysis and Discussion

This section will analyse the data and results in three parts. The first part will cover the results from the Basic Regressions (1) and (2) and their alterations (1a), (2a), (1b), and (2b). The second part will cover the aggregate regressions, that is, regressions starting with 3 and 4. The last part will compare the results from all regressions and discuss what conclusions regarding insider trades than can be drawn.

7.1 Regressions (1) and (2)

We find results with a 5 % significance on both 1 year and 6 months past excess return on insider trading volume. The coefficients are negative which indicates that insiders seem to buy (sell) stocks with poor (good) past performance. From our hypotheses, this would imply that these are stocks with negative (positive) sentiment. On all other time periods the results are not significant.

For the future excess return the coefficients are positive indicating the opposite, i.e. that insiders tend to buy (sell) stocks with good (poor) future performance. However, these results are not significant which is contrary to results from previous Swedish studies (Sjöholm and Skoog, 2006, Nogeman and Li, 2008). It is difficult to say why this is, however Sjöholm and Skoog use earlier data and both papers use event studies on shorter time periods.

The same analysis made on cluster transactions gives the same and stronger results with significance on 6 months past excess return of 0.1 %. Cluster returns are expected to give more significant results as these enhance the effects of increased trading in one particular stock by a number of insiders.

Deviating from these results, the transactions made by CEOs only show significant results on the 6 months future excess returns, and not on past returns. This indicates that stock prices tend to go up (down) after the CEO of the company buys (sells) the company's stock, but the CEO does not tend to buy when the stock price has fallen during a period of time.

From this one could draw the conclusion that the CEOs in general are better than other insiders at predicting future stock returns, implying that the CEO, due to his or hers position in the company, would know something about the company's fundamentals that other insiders are not aware of. Another explanation could be that the company's fundamental value has increased because the CEOs incentives are better aligned with the shareholders interests. A third take on this would be that sentiment of a stock increases when the CEO purchases the stock causing the share price to increase which could be seen as a result of signalling effect.

It is important to view these results in the light of the last decades market events. The insiders ability to understand the market and predict future returns is highly dependent on market conditions. Considering the last decade's market turmoil the results are bound to be affected by this.

7.2 Regressions (3) and (4)

The results of the aggregate net number of insider trades regressions all indicate the same thing; namely that there is a significant correlation between the long term excess market return and the aggregate past net number of insider trades. For the future excess market return the results are also significant on shorter time periods when the number of insider trades are aggregated over longer time periods.

The regressions run on the entire dataset give the strongest results for the future returns while the cluster and CEO regressions give weaker results. This makes sense as both cluster and CEO trades are generally closer tied to the specific company and regressing against the market as a whole thus makes less sense.

Therefore it is most interesting to look at the Basic Regressions (3) and (4) in this case, which provide quite a lot of significant results. In general we can see that the results are significant on the long term excess returns. For the future excess market returns we observe that insiders seem to be able to predict excess return in the market.

These results for the future return regressions are in line with Seyhun (1988), which suggests that insiders trade on market sentiment, rather than on illegal insider information, which would be firm-specific knowledge. Also in line with Seyhun (1988), the correlation between future return and aggregate insider trading are significant on long time periods, but our results show a trade-off between the time period of measuring the insider trades and the period for which the future return is estimated. That is, longer periods of market returns are significantly correlated also with shorter time periods of aggregate insider trading, and vice versa. This is not very surprising with the interpretation that every form of aggregate insider trading generates abnormal insider return over 1 year. If market sentiment moves slowly over time so that also longer periods of aggregate insider trades generate abnormal return over the 1 year time period, this pattern is explained.

Regarding the past excess market return, we observe that insiders tend to buy (sell) stocks that have been performing poorly (well) during a longer period of time. Here we do not have the same clear pattern regarding that using all data gives the most significant results. For example, the CEO transaction regression yields the most significant results, followed by the aggregated clusters, which both yields more significant results than the regressions using all values.

Regarding the regression of past return and aggregate insider trading, the results are significant but the pattern is not as clear. It seems that insiders buy (sell) when the market has generated negative (positive) abnormal return during longer time periods; 6 months and 1 year yield significant results. Worth noting is that the sign of the coefficient is not straightforward. Looking at longer time periods of aggregate insider trading, the short-term excess market return tends to be positive, although not significantly. This is in line with the results of Basic Regression (3), i.e. long term aggregate insider trading is correlated to future excess market return.

7.3 Discussion and Further Insights From Comparing the Results

The striking difference between the results of the aggregate regressions and the firm-specific regressions are the future returns. In the aggregate regressions, insider trades are strongly correlated with the excess future return of the market. In the firm-specific regressions however, only CEO trades show significant results for the future excess returns.

It seems that the CEO is the only one who can predict future stock return of the specific firm significantly. The average insider on the other hand, trades when the specific share has underperformed. He or she does not generate abnormal return against the market on a significant level.

The average insiders, aggregated in Basic Regression (3), are good at predicting the future return of the market, indicating that he or she trades when the share is under- or overvalued due to market sentiment. The fact that the results are less significant when we aggregate clusters and CEOs supports this notion of what type of information insiders do trade on.

However, when considering past excess return and aggregate insider trading, both the CEO and Cluster alterations yield more significant results than the Basic Regression (4). Looking at the CEO regression, the CEO buys (sells) when the market has underperformed (outperformed) rather than when the own firm's stock has underperformed (outperformed). When it comes to clusters, these buy (sell) both when the market has underperformed (outperformed) and when the own firm's stock has underperformed (outperformed),indicating a mix between the two trading patterns. These results again seem to indicate that the CEOs trade on other types of information than the average investor.

8 Conclusions

We cannot reject Hypothesis 1, it seems that stocks with low past performance are subject to insider trading by the average insider. The alterations to this Basic Regression (1) differ from these results indicating that different insiders trade on different types of information. Furthermore, our study shows that the CEO is the only type of insider that is able to predict firm specific future abnormal excess return.

We cannot reject Hypothesis 2 either, our study shows that aggregate insider trading is in fact positively correlated with the stock market excess return. Regarding the connection between aggregate insider trading and future excess market return the pattern is clear with increasing significance in increasing time periods of excess return and aggregate insider trading; when insiders buy (sell) on aggregate, future excess market return is positive (negative). The same clear cut pattern is not found regarding the connection between aggregate insider trading and past excess market return. Here we only find significant results for shorter periods of aggregate insider trading and longer periods of past excess return; insiders buy (sell) on aggregate when the market has underperformed (outperformed).

The results indicate that the CEO and the average insider trade on different types of information. While the CEO has more knowledge about the specific company and the future of it, the average insider are probably better at knowing when the company is undervalued due to market sentiment.

9 Suggestions for Further Research

An interesting finding in this thesis is the difference between the type of insider (CEO versus non-CEO). In line with this, and with ideas from Seyhun's research, it would be interesting to conduct the same type of regressions with a sector analysis. Since different types of industries are more or less difficult to understand and analyse, one can expect to find insider patterns differ between industries.

Previous research has suggested that insiders can have different reasons to sell their stock but generally only one reason to buy (Nogeman and Li, 2008) and that is that the insider believes that the stock price will rise. Other reasons than the insider sells than an anticipated price decline could be that the insider needs money or tax purposes. Therefore, another suggestion for further research, which could yield more significant results is to only run regressions on buy trades. This could be interesting especially since many of the more interesting analyses are made on tendencies rather than on statistically significant results.

10 References

10.1 Articles

Bloomberg L.P., (2010) Stiglitz Says Crisis Exposed 'Major Flaws' in Economics Ideas, Jan 2nd 2010

10.2 Journals

Baker, M., Wurgler, J., (2006), Investor Sentiment and the Cross-Section of Stock Returns, The Journal of Finance, vol. 61, Issue 4 (August 2006), pp. 1645-1680

Baker, M., Wurgler, J. (2007), Investor Sentiment in the Stock Market, Journal of Economic Perspectives, American Economic Association, vol. 21(2) (Spring), pp. 129-152

DeLong, J. B., Schleifer, A., Summers, L. H., Waldmann, R. J., (1990), Noise Trader Risk in Financial Markets, Journal of Political Economy 98:4, (August 1990), pp. 703-738

Finnerty, J. E., (1976), Insiders Activity and Insider Information – a Multivariate Analysis, Journal of Financial Analysis and Quantitative Analysis 11, pp. 205-216

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

Jensen, M. C., and Murphy, K. J., (1990), Performance Pay and Top-Management Incentives, Journal of Political Economy, vol. 98, no. 2 (April 1990), pp. 225-264

Lin, J.-C., and Howe, J. S., (1990), Insider Trading in the OTC Market, The Journal of Finance, Vol. 45, No. 4 (September 1990), pp. 1273- 1284

Lorie, J. H., Niederhoffer, V., (1968), Predictive and Statistical Properties of Insider Trading, Journal of Law and Economics 11, pp. 35-53

MacKinlay, C. A., (1997), Event studies in Economics and Finance, Journal of Economic Literature, Vol. XXXV (March 1997), pp. 13-39

Seyhun, H. N., (1986), Insider Profit, Costs of Trading, and Market Efficiency, The Journal of Financial Economics 16, pp. 189-212

Seyhun, H. N., (1988), The Information Content of Aggregate Insider Trading, The Journal of Finance, 42, pp. 129-141

Seyhun, H. N., (1992), Why Does Aggregate Insider Trading Predict Future Stock Returns?, Quarterly Journal of Economics, (November 1992), 107, no. 4, pp. 1303-1331

Summers, S. L., Sweeney, J. T., (1998) Fraudulently Misstated Financial Statements and Insider Trading: an Empirical Analysis, The Accounting Review, vol. 73m no. 1, (Jan 1998), pp. 131-146

Wahlström, G., (2003) Legal Insider Trading and Abnormal Returns: Some Empirical Evidence from Sweden, Financial Forum / Bank- En Financiewezen 2003/6, pp. 348-355

10.3 Legislation

Sweden, SFS 2000:1087, Act concerning Reporting Obligations for Certain Holdings of Financial Instruments (2000:1087)

10.4 Other publications

Seyhun, H. N., (1998). Investment Intelligence from Insider Trading. MIT: MIT press

Shleifer, A., (2000), Inefficient Markets: An Introduction to Behavioural Finance, Oxford: Oxford University Press

10.5 Theses

Li, F., Nogeman, J., (2008), Insider Trading on the Stockholm Stock Exchange, Stockholm School of Economics, Master's Thesis in Finance

Sjöholm, M., Skoog, P., (2006), Insider trading on the Stockholm Stock Exchange, Stockholm School of Economics Master's Thesis in Finance