The Privilege of Possessing Inside Information

- A study of insider trading in Denmark

by

Jakob Stein Bügel

and

Julie Runge Jørgensen

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Supervisor: Professor Steffen Andersen

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Abstract

We construct and use a unique dataset consisting of high quality Danish register data to study insider trading prior to the release of corporate announcements in Denmark. The insider trading behavior is studied by conducting an event study and a pooled cross-sectional regression study. We find that the trading activity of corporate insiders rises significantly shortly before the release of a company specific announcement and that this trading activity predicts the pricing impact of the announcement. This pre-announcement pattern persists when controlling for socioeconomic factors. Furthermore, we document that corporate insiders and their families obtain substantial abnormal returns when trading before announcements. No such returns are obtained by the outside population, which indicates that a subset of corporate insiders and their families possesses and exploits non-public information.

Foreword

In May 2017 we started working towards what would become our master's thesis. After a year of writing thousands of lines of code in Stata, Python, and SQL we have reached the point where this foreword is the last paragraph missing in our thesis. We would like to thank our supervisor and employer, Steffen Andersen, for giving us a glimpse of the world of research and carefully helping us along the way. We have enjoyed the journey, and we are happy that you made it possible for us to write together. We would furthermore like to thank Allan Grønlund and his research team in Aarhus for helping us scrape the CVR register. Additionally, we are grateful to Frederik Lund-Thomsen who provided us with the Danish Financial Supervisory Authority's dataset on corporate announcements of Danish listed companies. Finally, we are thankful to the entire FiRL research team who has contributed with useful advice, guidance, and ideas throughout our writing process.

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Introduction

Imagine knowing something about the future of a stock that the market does not – the opportunities for profit are infinite! This is the daily life of many key employees of listed companies, as they are exposed to information about their company that the market does not have access to. We investigate whether some corporate insiders in Denmark give in to this temptation and trade before information is made available to the market.

There are two main views on insider trading. The most prevalent view is that insider trading is unfair (Moore, 1990). According to Moore, insider trading is by many considered to be “the very symbol of ethical decay in business”, as corporate insiders exploit non-public information to their own gains at the cost of the general market (ibid). On the other hand, believers of the efficient market hypothesis argue that if markets are efficient, insider trading information should already be priced into the market as soon as one corporate insider trades on the information. As a result, banning insider trading leads to markets being less efficient (Fishman & Hagerty, 1992). If markets were efficient and unregulated, insider trading would thus be unprofitable according to this school of thought. In most countries, including Denmark, insider trading based on non-public information is illegal. Yet, despite this fact several papers have found systematic insider trading patterns prior to firm specific announcements (John & Lang, 1991), (Augustin, Brenner, & Subrahmanyam, 2015), and (Jain & A. Sunderman, 2014).

This master’s thesis was incepted as a function of a gap in the published literature on insider trading. The insider trading literature is divided into two branches. The first branch studies databases on reported insider transactions, and constructs trading strategies contingent on mimicking the trades of all reported insider transactions. The second branch of the insider trading literature has studied the transactions of convicted insider traders using court papers. Here, puzzles such as network effects, how illegal insider traders attempt to hide their trades, and realised returns are investigated. The data used by the first branch is limited to only observing those transactions reported by corporate insiders, and is blind to trades conducted by relatives of a corporate insider or people who have received non-public information through their network. On the contrary, the results of the second branch are biased by not observing the transactions of insiders who managed to avoid the attention of the authorities. To our understanding no published paper has yet studied insider trading using a dataset containing all individual stock market transactions of an entire economy.

Together with our supervisor, Steffen Andersen, we have collected a unique dataset containing all personal stock market transactions of all Danes from SKAT, names of top management, board members and accountants from the CVR registry, a list of all firm specific announcements for listed companies in Denmark from the Danish Financial Supervisory Authority, daily prices on all listed Danish companies, and lastly register data from Statistics Denmark. This dataset allows us to study both reported insider transactions, non-reported insider transactions, transactions of the families of insiders, convicted insiders, non-convicted insider traders and studies of professional networks. As a result the dataset allows for a more nuanced study of insider trading compared to previous scholarship.

No research or data is perfect. As a result, the dataset is prone to the following limitations: firstly, the dataset does not contain transactions for Danes using foreign bank accounts. This limitation is also shared by both the public records literature and potentially the court case literature. Secondly, our dataset does not contain legal proof of whether the insider trading pattern is illegal or not. Thirdly, the current state of the dataset has no way of identifying which trades were reported to the Danish financial authorities. Fourthly, the dataset does not contain data on trades executed through private companies, implying that a corporate insider can remain hidden from this dataset if trades are executed through a holding company. Despite these shortcomings our study can provide a valuable addition to the insider trading literature, as the dataset is richer in detail compared to what has been accessible to previous scholarship.

To study this unique dataset we have formulated the following research question:

Research question: *"to which extent can it be argued that corporate insiders and their network are in a privileged position compared to the general public prior to the release of corporate announcements?"*

In order to answer this research question we test the following hypotheses:

> Hypothesis 1: *Insiders' trading activity rises prior to the release of corporate announcements.*
> Hypothesis 2: *Corporate insiders are better at predicting the direction of a significant announcement than outsiders.*
> Hypothesis 3: *Differences in trading patterns are not explained by socioeconomic factors.*

Hypothesis 4: *Corporate insiders, their network, and family earn higher returns than the overall population prior to company specific announcements.*

We find that the trading activity of corporate insiders rises significantly relative to other trading groups prior to announcements, and that a significant fraction of trades are in the same direction as the outcome of the significant corporate announcements. This increase of trading activity persists when controlling for socioeconomic factors. Lastly, we find that corporate insiders and their families make substantial abnormal returns prior to corporate announcements. These findings could imply that some traders exploit non-public information for private gains, which could be of interest for regulators.

To answer the research question, the underlying hypotheses, and derive the abovementioned findings, we split the thesis into seven sections. The first section studies what the Danish law defines as insider trading and other legal reporting requirements related to insider trading. The second section consists of a theoretical and an empirical literature review. In the theoretical literature review we investigate whether insider trading is profitable, by studying the efficient market debate. In the empirical subsection existing research from both the public records branch of the literature and the court case data branch is investigated. In the third section we describe, discuss, and summarise the data used in our study. The fourth section outlines the choice of methods for this thesis. The method section includes discussions of event studies, aggregation methods, pooled cross-sectional regressions, and returns. This methodological toolset is then used in the fifth section – the results section. We divide the results section into three parts. Firstly, we conduct an event study and investigate whether corporate insiders exhibit significantly different trading patterns compared to other trading groups. Furthermore, we study whether corporate insiders trade in the right direction of corporate announcements. In the second subsection of the results section we investigate whether the difference in trading behaviour of various groups of potential informed and uninformed traders persists after controlling for socioeconomic factors such as job type, education, and income. The last subsection of the results section contains an analysis of both abnormal and absolute returns earned by the different trading groups. In the sixth section we address potential caveats of our study and discuss further research. Lastly, we summarise our study and conclude on the results.

Legal Definition of Insider Trading

In this section we seek to understand the European and thereby Danish regulatory environment concerning insider trading. The main body of law text is located in the European Market Abuse Regulation (MAR). In order to understand the regulatory framework this section is divided into four parts: firstly we investigate what the MAR defines as insider information, secondly we outline what is defined as insider trading, thirdly we explore existing laws regarding reporting standards related to insider trading, and fourthly we review how to distinguish between legal and illegal insider trading.

Insider Information Definition

The Market Abuse Regulation (MAR) (Regulation (EU) No 596/214) was enacted as the leading European regulatory framework on market abuse by the European Parliament in 2014 (European Parliament, 2014). In 2016 the regulatory framework came into force in Denmark, replacing the existing Danish rules on market abuse from the Danish Securities Trading Act with only minor adjustments (Plesner, 2016). According to MAR, the regulation: *"establishes a common regulatory framework on insider dealing, the unlawful disclosure of inside information and market manipulation (market abuse) as well as measures to prevent market abuse to ensure the integrity of financial markets in the Union and to enhance investor protection and confidence in those markets"* (European Parliament, 2014). As a result, we find it useful to base the legal definitions of insider trading on the MAR document, as it is the main regulatory document on insider trading in the Eurozone.

According to article 7, 1,a of the MAR, insider information can be classified into four parts (European Parliament, 2014) (Danish Financial Supervisory Authority, 2017a):

i. Information of precise nature,
ii. Information that directly or indirectly involve one or more issuers or one or more financial instruments,
iii. Information that has not been published,
iv. Information that if published could significantly impact the price of financial derivatives or derivatives, relating to the information,

Thus, insider information constitutes unpublished information that is so specific to a certain company, that if published would lead to significant changes of the stock price. Information of precise nature is defined as information describing a set of past, future, or present events or circumstances that is so specific that one can infer the market impact of these events or circumstances (European Parliament, 2014). Furthermore, this information should be informative to the extent that it is understandable and useful to a "reasonable investor" in making informed investment decisions (ibid). However, as is also stated by the Danish Financial Supervisory Authority, the definitions surrounding what constitutes insider information are often rather intangible (Danish Financial Supervisory Authority, 2017a). For instance, in inferring whether the event has a potential impact on the future stock price, one has to interpret whether the information could be used by a "reasonable investor". Thus, one has to make assumptions concerning who the average reasonable investor is, and infer whether the information would be useful for such a person. Furthermore, it is up to interpretation whether it is "reasonable" or not that the future event will occur (ibid). This makes it challenging for our study, and for the Danish Financial Supervisory Authority to assess what constitutes insider information. Therefore, we have no intention of assessing the legality of pre-announcement trades.

Thus, we learn that inside information is information that is unpublished, can help inform a reasonable investor in making investment decisions, and that may lead to significant price change of the security when the information is published. However, the definition of what constitutes insider information is case specific, vague, and thus hard to pinpoint. It is now relevant to investigate what defines insider trading.

Insider Trading Definition

According to article 8 of the MAR insider trading or "insider dealing" is defined as:

"(...) insider dealing arises where a person possesses inside information and uses that information by acquiring or disposing of, for its own account or for the account of a third party, directly or indirectly, financial instruments to which that information relates. The use of inside information by cancelling or amending an order concerning a financial instrument to which the information relates where the order was placed before the person concerned possessed the inside information, shall also be considered to be insider dealing." (European Parliament, 2014).

Thus insider trading is carried out by an individual in possession of inside information who trades or cancels planned trades on a security related to the company. What is worth noticing is that the MAR specifically writes a person in possession of inside information. This implies that it is also illegal to trade on inside information if the trader is not a corporate insider. Furthermore, the MAR dictates that the insider trading definition also includes recommending or inducing other people to trade on the given information (European Parliament, 2014). As a result, it is also illegal to disclose inside information to any other person that is not related to the event through employment, a profession or duties (ibid). But how does one make sure that insiders do not trade on inside information prior to corporate announcements? The next paragraph will investigate how inside information is registered in accordance with the MAR.

Public Disclosure of Inside Information and Insider Lists

According to the article 17 of MAR: *"An issuer shall inform the public as soon as possible of inside information which directly concerns that issuer"* (European Parliament, 2014). This implies that information should be announced as soon as possible to the public. This marks a slight change in formulation compared to the Danish Securities Trading act, which specified that publishing inside information should first occur once a scenario or event has been manifested (Danish Financial Supervisory Authority, 2017a). As a result, the Danish Financial Supervisory Authority has interpreted this change in formulation to mean that companies have to publish inside information to the public faster and prior to the occurrence of the event. For our study it is worth stating that whether inside information is leaked slightly faster does not impact the fact that the market obtains unexpected information and how the market reacts on it.

Apart from the requirement to quickly disclose inside information to the public and the Danish Financial Supervisory Authority, MAR article 18 also specifies that companies ought to provide inside lists to the supervisory authorities (European Parliament, 2014). An inside list consists of all relevant individuals both internally (employees etc.) and externally (consultants, accountants etc.) who have access to private information. This list should be constantly updated, and be available to the authorities if requested (European Parliament, 2014). Thus, from a regulatory perspective, there are relatively high requirements for documenting insider information and those who possess it. As a result, we can learn that the regulation on insider trading is extensive, and that there are several sources of reporting that the companies ought to do.

Finally, in Denmark central corporate insiders are obliged to report trades in their respective company if the total trading volume exceeds 20,000€ yearly (Danish Financial Supervisory Authority, 2017b). The insiders have three working days to report each trade to the authorities, after this limit has been exceeded (ibid). Whether they report or not does not bias our study, as our dataset contains all stock market transactions by individuals in Denmark. Furthermore, corporate insiders are not allowed to trade in their own company within 30 days of the release of a financial statement (ibid).

The Difference Between Legal and Illegal Insider Trading

From the previous paragraphs we learn that buying, selling or annulling trades based on inside information, which at the time of trade is unknown to the market, is illegal, as it poses an unfair advantage to the insider vis-à-vis the market. However, that doesn't imply that corporate insiders never conduct trading in their respective companies. Corporate insiders are allowed to trade when they do not have access to important information not known to the market (Clark, 2014). Thus, in order to investigate whether a trade by a corporate insider is legal or illegal, the authorities have to investigate whether the person had access to inside information, and whether he had this information in mind when conducting the trade (ibid). According to Clark, illegal insider trading is a challenging crime to prove, as firstly it is hard to determine that the insider possessed the relevant information prior to the trade, and secondly it can be cumbersome to prove that a certain individual was responsible for the trade, as such traders often hide their trades (ibid). Furthermore, in court cases direct evidence of illegal insider trading is rare. Unless the defendant confesses or there is access to eyewitnesses, the boundary between legal and illegal insider trading is blurred (ibid). Because of these legal caveats we are not able to nor have any interest in judging people who trade before announcements to be illegal or legal insiders. For this paper one should understand the word "insider trader" as a person who trades in his own company.

Literature Review

In this literature review we investigate existing contributions to the academic field of insider trading. We identify and highlight the merits and gaps of the existing scholarship, and comment on how to breach some of these gaps. Inspired by the literature, we formulate four hypotheses and gain insights on how to investigate these. The literature review is divided into three main subsections. In the first subsection, we investigate existing economic theory, prevailing scholarship on the centrality of future information on stock prices, and the theory of market efficiency. This is done in order to highlight why trading on non-public information can potentially be highly profitable for insiders. The second section reviews empirical scholarship regarding insider trading, and is divided into two parts. The first part investigates the literature on public records of insider transactions, while the second part reviews findings from studies on convicted insider traders. The overall purpose of this literature review is to identify the main breakthroughs of existing scholarship and make a humble research proposal on how to improve the knowledge on insider trading further. This is done in the third and final section of the literature review.

Theoretical Review: the Centrality of Information in Relation to Stock Pricing

It has for long been established that information is a key parameter in pricing financial assets, yet whether prices reflect all available information is still a heavily debated issue. Eugene Fama, a main proponent of the Efficient Market Hypothesis, argues that: "A market in which prices "fully reflect" available information is called efficient" (Fama, 1970). An efficient market is one where prices provide accurate signals for resource allocation. According to Fama, the efficient markets hypothesis holds, only with a limited set of observations speaking against it (ibid). The efficient market hypothesis was the sole theory used to model stock market return development through random walk models in asset pricing theory until the 1990s (Degutis & Novickytè, 2014). Fama defines three variants of the efficient market hypothesis: the weak form version rests on the assumption that security prices reflect all historical information, the semi-strong formulation builds on the notion that security prices reflect all public available information in the market, and the strong form version states that security prices reflect the entire subset of both inside and public information (ibid). The strong form version thus predicts that corporate insiders would not be able to obtain abnormal returns from insider trading, as the information is already reflected in the price of the security (Wong, 2002) (Rozeff & Zaman, 1988). Therefore systematic insider trading prior to announcements should not be prevalent, as insider information would immediately be priced into the market.

It is far from everyone that shares Fama's view that prices reflect all public and private information. Stiglitz & Grossmann show in their 1980 paper that prices theoretically cannot reflect all information in the market if information is costly to acquire. If information is costly to acquire, no one would pay to acquire the information and as a result the information would not be available to the market (Stiglitz &

Grossman, 1980). Furthermore, Shiller argues that classical financial theory should learn from behavioural finance as stock prices fail to embed the best information (Shiller, 2001). Thus, according to Shiller expectations, emotions, and irrational factors have a substantial impact on market prices. The market is therefore not efficient and may not encompass all available information (ibid). Lastly, Pedersen places himself between the efficient market hypothesis and the inefficient school of thought and argues that markets are efficiently inefficient (Pedersen, 2015). Pedersen argues that market prices initially underreact to company specific announcements, and therefore makes it possible for a sophisticated and fast investor to earn abnormal returns - even from trading on public information (ibid).

The academic literature is thus divided on whether markets are efficient i.e. the degree to which information explains stock price movements. Despite this debate, all models agree that information about the future is central to stock price valuation. With the exception of the strong form efficient market hypothesis, we therefore learn that trading on non-public information can yield significant abnormal returns. Finding evidence that corporate insiders generate positive abnormal returns from trading prior to corporate announcements suggests that markets are not strong form efficient.

Empirical Review: Studies on Insider Trading

In this section we review the literature on insider trading, firstly by looking at studies on public records, and then by looking at studies on court papers. These studies serve as the main research inspiration for our master's thesis.

Studies on Official Records of Insider Trading

A substantial and influential segment of the insider trading literature has focused on the informativeness related to the trading patterns of corporate insiders. A subsection of this branch of literature has attempted to create trading strategies based on unusual insider trading volumes and systematic patterns in order to obtain alpha (abnormal) returns. If one can obtain alpha by mimicking trades conducted by corporate insiders, the market cannot by definition be strong form efficient as postulated by Fama. Furthermore, it is of high interest to investigate this branch of literature, as a successful trading strategy based on following insiders implies that corporate insiders also make abnormal returns, which could indicate that they trade on non-public information.

A substantial amount of papers have from the 1950s to the early 2000s looked at legal insider trading by devising trading strategies based on the cross-sectional variation of insider trading activity on firm level (Cohen, Malloy, & Pomorski, 2012). Among the first papers that find cross-sectional evidence on the profitability of mimicking trades by insiders is the 1968 paper by Lorie & Niederhoffer. The authors find, by measuring the buying and selling frequency of corporate insiders at firm level, that a period of rapid stock accumulation increases the probability of stock outperformance within six months (Lorie & Niederhoffer, 1968). A similar pattern was discovered for selling (ibid). Furthermore, the authors find that a shift from a long streak of stock purchase to stock sale has information value regarding the expectations of corporate insiders (ibid).

In a similar vein, prominent papers such as (Jaffe, 1974), (Seyhun, 1986), (Rozeff & Zaman, 1998), (Lin & Howe, 1990), and (Lakonishok & Lee, 2001) have studied cross-sectional variation at firm level. Jaffe attempts, in his 1974 paper, to widen the sample size used by the Lorie & Niederhoffer and includes transaction costs in the analysis (Jaffe, 1974). The author finds, similar to Lorie & Niederhoffer that corporate insiders derive profits from possessing special information; this is directly in contrast to the predictions of the strong form efficient market hypothesis (ibid). However, Jaffe finds that, when including transaction costs, abnormal returns from mimicking trades of corporate insiders are only positive and significant after periods of "intensive trading" with a holding period of 8 months (Jaffe, 1974). Thus, we learn from Jaffe: trades by insiders yield above normal returns, a larger trading activity by insiders is an informative signal of abnormal returns, and mimicking trades by corporate insiders is costly due to substantial transaction costs. The remaining scholarship places itself between Jaffe and the Lorie-Niederhoffer study by using slight modifications to measure returns and firm-level insider trading activity. Despite the differences in findings, and slight deviations of methodology in the 1960-2000 papers, Seyhun summarizes the findings of this branch of literature by concluding that several different trading rules based on insider trading patterns can yield abnormal returns (Seyhun, 1998). Thus, on the aggregate insider trading activity on firm level can serve as a predictor of the future returns of a company - in contrast to the predictions of the strong-form efficient market hypothesis.

The above mentioned scholarship used trading activity criteria in order to calculate abnormal returns at the firm level (Jeng, Metrick, & Zeckhauser, 2003). However, by basing the screening process for signals on firm level and by disregarding the return on each individual insider trade one forgoes: 1) to measure the actual realised return of a trade by a corporate insiders and 2) to measure the returns of non-reported insider trades. In their 2003 paper Jeng, Metrick & Zeckhauser estimate the returns of corporate insider traders using performance evaluation, thus breaching the first gap of the abovementioned scholarship (Jeng et al., 2003). According to the authors, the use of intensive trading criteria embodied by the before mentioned scholarship is flawed when one wants to study the returns realised by corporate insiders: firstly, using stocks as the main unit of analysis makes it impossible to determine the value-weighted return of all trades. Secondly, stocks with intensive buying or selling might constitute a small non-representative fraction of insider trading. Thirdly, having a certain time period to measure insider trading activity implies that stock returns are first measured when the screening interval ends, and as a result one cannot measure the return of the first trades in the screening interval (Jeng et al., 2003).

In order to overcome these issues Jeng et al. instead use performance evaluation on value-weighting portfolios to assess the returns obtained by corporate insiders (Jeng et al., 2003). They establish two "shadow" portfolios; one consisting of all purchases of stocks by insiders and one consisting of all sales by corporate insiders (ibid). A stock is held in the portfolio for 6 months where the start date is specified as the day the stock order is executed by the corporate insider (ibid). Constructing two portfolios allows the authors to take account of performance factors such as size, momentum, value, and market risk of the insider trades. The authors find that the monthly abnormal return for the purchase portfolio, using several different risk adjusting measures, ranges between 52 and 68 basis points for a 6-month holding period (ibid). This result is both economically and statistically significant. Furthermore, the returns within the first five days after the trade amount to a quarter of the 6-month returns. Half of the return is generated within the first month. This can either suggest that corporate insiders have a good understanding of their company's performance in the short term, or that investors with a trading strategy based on mimicking trades by corporate insiders can move the market. The authors find that the sales portfolio has no abnormal return. Thus from this paper, we learn that there is an empirical basis for looking at insider trading on the very short term, and that insider trading is potentially centered on the buy-side.

Apart from the studies of returns stemming from inside trades, the reported public trading data has also been used to investigate the trading patterns of corporate insiders around important company specific announcements. This is of special interest to our study, as we analyse trading by different groups of informed and uninformed investors around company specific announcements. Insider trading activity was found, by Watson and Young, to spike sharply both long before and shortly before merger announcements in Australia in the 1996-1998 period (Watson & Young, 1999). According to Watson and Young the trading spike right before merger announcements suggests a "certain amount of disregard for the regulatory authorities" (ibid). Likewise, Augustin, and Brenner and Subrahmanyam find evidence of insider trading, by the use of options, around merger and acquisition announcements (Augustin et al., 2015). Furthermore, in relation to dividend announcements, John & Lang find that insider trading prior to dividend announcements serves as an explanatory signal for the market reaction to a dividend announcement (John & Lang, 1991). In a similar vein, Ke, Huddart and Petroni find evidence of systematic insider trading patterns up to two years before breaks in sequences of earning increases in the income statements of companies (Ke, Huddart, & Petroni, 2003). Lastly, empirical evidence shows that corporate insiders also increase stock purchases up to a year prior to corporate spinoffs (Charoenwong, Ding, & Pan, 2016). Thus we learn that there is rich evidence for increased insider trading activity around announcement: insider traders are not just investing based on long run information but also on information related to crucial announcements located in the short run.

A recent contribution to the literature, on public records of insider transactions, is the paper of Cohen, Malloy and Pomorski. Compared to previous scholarship the focus of the authors is located at the micro-level, where they investigate the trading patterns of each individual corporate insider instead of looking at insider trading at the firm level (Cohen et al., 2012). The authors divide the trades of corporate insiders into opportunistic and routine trades using a simple identification strategy: routine trades are defined as trades by corporate insiders that have been executed within the same month the last three years. All other trades, that do not follow this pattern, are classified as opportunistic trades (ibid). Using this identification strategy, which approximately divides the sample in two equal sizes, the authors devised a long-short trading strategy that goes long on purchases and shorts sales by the two groups. The authors find that mimicking trades conducted by routine traders earns -20 bps per month for a value-weighted portfolio and 43 bps per month for an equal-weighted portfolio - both returns are insignificant at the 5% level (Cohen et al., 2012). In contrast, the opportunistic trade portfolio earned 82 bps from a value-weighted portfolio, and 180 bps per month for an equal-weighted portfolio (ibid).

From these results we learn three things: firstly, that corporate insiders trade for other reasons than exploiting inside information; these reasons can be liquidity and diversification (Cohen et al., 2012). This type of corporate insider is a routine trader and mimicking her does not yield significant abnormal returns (ibid). Secondly, that following opportunistic traders can yield large significant returns, indicating that trades of opportunistic trades may involve the exploitation of non-public information (ibid). Thirdly, we learn that without identifying opportunistic and routine trades one exposes oneself to significant background noise from routine trading when testing insider patterns related to announcements and returns (ibid).

In extension, the authors find that when it comes to predicting the outcome of a future company announcement, the trading pattern (buy for a positive announcement, sell for a negative announcement) of opportunistic trades has explanatory power in predicting whether the future announcement increases or decreases firm value (Cohen et al., 2012). Furthermore, the authors find that the trades executed by opportunistic traders were more sensitive to news regarding insider trading and were more likely to end up in SEC[1]-investigations compared to routine trades (ibid). Lastly, the authors find, similar to the firm level literature, that larger trading intensity predicts positive and significant abnormal future returns. As a result, we learn that there is a wide acceptance of studying insider trading intensity, such as in the form of volume, when it comes to measuring insider trading close to announcements. Furthermore, we also learn that there are visible trading patterns related to corporate announcements on the micro level.

Summary and Comments on the Insider Trading Literature Based on Public Records

From the public records data we learn that there appears to a strong academic acceptance that, on the aggregate, corporate insiders obtain substantial abnormal returns, implying that they possess non-public information. This indicates that financial markets do not appear to be strong form efficient. Furthermore, we learn that trading intensity using trade volume measures, both on micro and firm level, is a significant predictor for higher future returns and a predictor for announcements having a

[1] Securities and Exchange Commission

[2] International securities identification number

[3] Financial literacy here is defined as graduated or trained in finance or economics. This includes individuals having

significant effect on the stock price. Additionally, insider trading is present both short before corporate announcements and up to two years before a crucial announcement. The extent to which one can extract knowledge from trades by insiders and generate abnormal returns is, however, questionable on firm level. Nevertheless, one can obtain high abnormal returns by filtering routine trades out of the sample of insider transactions. We thus learn that insiders trade for a variety of reasons: for liquidity reasons, for diversification, but also for reasons involving profiting on private information.

Critique of the Public Records Literature

While we have discovered useful insights from studying the public records literature on insider trading it is also worth understanding its gaps. The scholarship on public records can be significantly biased for four reasons: firstly, one only observes the trades that are actually reported to the authorities. Insider trading is illegal, and as a result it is reasonable to imagine that potential insider traders try to hide their activity by either not reporting, using different trading accounts, or by making relatives trade etc. Secondly, regulators often require corporate insiders to report trading only after they have traded a certain yearly amount in the company stock. In Denmark this cut-off is 20,000€. The public records literature thus suffers from missing observation bias for small trades. Thirdly, the MAR defines insider trading as trades conducted by individuals in possession of non-public knowledge. As a result, relatives, friends, or acquaintances of a corporate insider also fall within the insider trading classification if information has been leaked. Thus, using public records might only serve as a small subset of the total insider trading activity in an economy. Fourthly, there are a variety of motivations for corporate insiders to trade other than for the incentive of profits. By not including information such as court data, one fails to distinguish which trades are a function of coincidence and which are not. We thus find it problematic that this branch of literature has not attempted to widen their data sources by, for instance, including court cases that could involve trades initially hidden from regulators. To understand the phenomenon of insider trading one must investigate the entire landscape.

Studies Based on Illegal Insider Trading from Court Cases

A second branch of the insider trading literature focuses on court cases on insider trading. These studies are often based on hand-collected datasets from reading through official court documents. Using such data allows a researcher to investigate past trading behaviour of convicted insiders, how insider information is spread, and how much these convicted corporate insiders earn from trading on non-public information. Obviously, the fact that data is hand collected implies that few studies have been conducted on the area, as the data is not as easily accessible as public records data.

Insider trading prior to corporate announcements explains 40 to 50 percent of the pre-announcement price run-up 30 days before announcements (Meulbroek, 1992). This suggests, that illegal insider trading occurs within 30 days prior to announcements. In her 1992 paper, Meulbroek studies insider trading by using American court documents from the SEC (ibid). She finds that the total trading volume on an insider day is higher than expected (ibid). This is interesting, as the insider trading pattern constitutes most of the unusual volume (ibid). This result complements the findings from the public records literature that find that insider traders increase trading volume prior to important announcements. Thus, in mapping insider trading activity, trading volume is an important metric. Related to trading volume, McInish, Frino, & Sensenbrenner (2011) find that convicted insider traders were more likely to perform illegal insider trades during high trading volume days to hide their trades. This might suggest that insider trading is more severe in corporations that are large in terms of trading volume, as it makes it easier to "blend" into the crowd.

Despite the fact that insider trading is classified as trades placed by any person possessing private information, almost no studies investigate how people external to a company exploit information for profit motives. One exception is Ahern's 2017 paper (Ahern, 2017). Using a hand-collected data set, stemming from court cases in the US, Ahern finds that convicted insider traders earn returns of 35% over 21 days (ibid). Thus, once again returns are high and significant even in the very short term. Ahern's paper is unique because it traces how non-public information disseminates throughout the network: from the corporate insider to buy side investors (Ahern, 2017). From the court cases, 183 insider networks are identified between 1996 and 2013. Ahern documents that knowledge flows through these networks through relations such as family ties, friends, and geographic proximity. On average, buy side investors are reached after the third link in the network. This is interesting, as buy side investors often have significant capital to invest in the stock. As a result, his paper shows that by conducting network analysis one could potentially obtain a better insight into insider trading patterns, and that screening the trades of corporate insiders solely excludes a large fraction of illegal insider trading. In our study we investigate such network effects, both from family ties and professional relations.

Unsurprisingly, Ahern finds that the average insider trader is a top executive or corporate manager. Lawyers, board members, low-level employees and buy-side managers are, however, also well represented (Ahern, 2017). The average insider is 44.1 years old, has more expensive housing than the population and zip code average, and only 9.8% of insider traders are women (Ahern, 2017). This can suggest that women are less likely to trade on inside information, that women are less likely to be involved in the networks, or may stem from a relatively lower representation of women in boards (ibid).

Insiders trade large amounts: Ahern finds that the median amount traded is $226,000. Furthermore, the median profit equals $72,400. The large trade sizes are on average invested in companies with market values over $1 billion (Ahern, 2017). Similar to past scholarship, Ahern postulates that a large market cap is beneficial for insider traders, as a large trading volume makes it easier to remain unnoticed (ibid). However, Ahern states that his data set is potentially subject to bias, as there is a significant underrepresentation of small trades (ibid). This can mean two things: either that small trade sizes make it harder to get caught, or that insider traders on average trade large amounts, as trading small amounts leads to less profits. Related to the public records scholarship, Ahern finds that insider trading increases pricing efficiency, implying that companies with significant insider trading move closer to their fundamental value. This suggests either that the market is able to identify informative trades or that the trades from the corporate insiders are able to impact the market prices directly.

Summary and Critique of the Illegal Insider Trading Literature

From the literature on illegal insider trading we find that there appears to be evidence that illegal insider trading is more prevalent in corporations with a large market capitalization. Illegal insiders typically make high returns within a short time frame. Furthermore, convicted insider traders traded on days with large trading volumes in order to try to blend into the crowd. As a result, measuring trading volume and insider traders' share of trading volume can be an interesting measure when trying to understand insider trading patterns. Measuring trading volume and returns of only corporate insiders might, however, not be an efficient way to study insider trading behaviour. As we learn from Ahrens network analysis, a significant proportion of insider traders are external to the company. As a result, one should attempt to map the relatives or professional relations of corporate insiders too.

However, the studies of illegal insider trading potentially suffer from bias. Firstly, as reported by Ahern, there is a small fraction of small trades in his data set (Ahern, 2017). This implies that there might be several trades that are of a size small enough not to be detected by authorities. Secondly, as stated by Clark (2014) insider trading is a difficult crime to prove, and as a result one might suffer from sample size bias if research is conducted only on convicted corporate insiders. Furthermore, the distinction between legal and illegal insider trading is blurred: whether these trades are based on knowledge of a certain event that increases firm value (which is what regulators typically classify as insider knowledge) or whether corporate insiders trade on their impression of the state of the company is difficult to prove. As a result one must attempt to study the entire set of transactions of both legal and illegal insider trades in order to understand the Danish insider trading environment.

In conclusion, studying public records of insider trading or court cases in vacuum is not sufficient in understanding the phenomenon of insider trading. Instead one should try to acquire trading data for the entire population of trades in an economy, and then conduct analysis similar to both branches of scholarship.

Lessons Learnt from the Literature: Formulation of Hypotheses

From the theoretical section, we learned that if markets are efficient then insider trading should not be a prevalent phenomenon. To explore this, we formulated the research question: *"to which extent can it be argued that corporate insiders and their network are in a privileged position compared to the general public prior to the release of corporate announcements?"* This research question is broad, as the theoretical literature is heavily divided on the profitability and therefore prevalence of insider trading. In order to answer this research question we have devised four hypotheses.

To investigate whether corporate insider trading is prevalent prior to announcements, we are inspired by the findings of previous scholarship, both within public records and court data. Both branches find evidence of increased insider trading activity (in form of trading volume) prior to announcements. Furthermore, some of these studies show that the corporate insiders trade in the correct direction of such announcements. To investigate and potentially replicate these past findings for our dataset, the following two hypotheses are formed:

H1: *"Insiders' trading activity rises prior to the release of corporate announcements."*

H2: "*Corporate insiders are better at predicting the direction of a significant announcement than outsiders.*"

The advantage of our study is that we have had access to register data on the Danish population. This enables the investigation of whether socioeconomic factors or access to non-public information are the main drivers of any differences observed between the various types of traders. This has been beyond the scope of previous literature. If information is the main driver, one should still see differences in trading behaviour prior to announcements when controlling for socioeconomic factors:

H3: "*Differences in trading patterns are not explained by socioeconomic factors.*"

Finally, both the public records and court data literature find that corporate insiders earn substantial abnormal returns. It is of high interest to investigate the average return of a potentially informed trader. Furthermore, as it has been shown that insider trading is not limited to corporate insiders, we also investigate the returns for families of insiders and their professional network, as both groups have a chance of obtaining non-public information from the corporate insiders. This forms the fourth and final hypothesis of our master's thesis.

H4: "*Corporate insiders, their network, and family earn higher returns than the overall population prior to company specific announcements.*"

As all hypotheses involve empirical investigation, it is now relevant to discuss and explain the data used in our thesis.

Data

This section is split into three parts: the first part describes and discusses the different data sources used in our study and how they were obtained. The second part explains how the final datasets were cleaned and constructed, reviewing any potential data issues. The final part provides key summary statistics.

Data Sources

In this section we go through the five main data sources used to construct our dataset, how they were cleaned, and how they were structured. We use data from the CVR register to identify individuals associated with the Danish companies listed on the Copenhagen Stock Exchange. SKAT has provided individual trading data for individuals trading in companies on the Copenhagen Stock Exchange in the period 2012 to 2016. From the Danish Financial Supervisory Authority, we received information on all corporate announcements and headlines posted by or concerning the Danish listed companies. Data on daily prices together with the link between a stocks ISIN[2] number and the corresponding CVR-number for the company were obtained from Datastream. These datasets were sent to Statistics Denmark, where we linked the information to personal characteristics for all individuals Denmark.

The CVR register

The CVR register has since 1999 been the authoritative register for all registered companies in Denmark (The Danish Central Business Register, 2018a). The companies themselves report their data, using their unique company identifier (the CVR-number) (The Danish Central Business Register, 2018b). This concerns almost every administrative aspect of the companies. The data relevant for our study regards people who are affiliated to companies that are traded on the Copenhagen Stock Exchange (Nasdaq Copenhagen), and therefore are likely to possess information about said company that the market might not have. The CVR register is available online, and anyone can carry out searches for specific companies.

However, downloading a larger amount of information, say, all of the data from the CVR register, is slightly more complicated, and is done by using ElasticSearch (The Danish Central Business Register, 2018b). In order to obtain information this way, permission from the CVR register is needed. Neither of this paper's authors are experts in ElasticSearch. Allan Grønlund, Postdoc from Aarhus University's Department of Computer Science, and his research team were kind to provide us with such expertise, sharing code they had used to download a large dataset from the CVR register. Using this code, we were able to set up an SQL database with all the information that was available from the CVR register.

[2] International securities identification number

As with all raw data, a significant amount of cleaning was necessary in order to obtain the desired data structure. The raw data is divided into several different SQL tables, each storing different types company specific information. Each company has a unique company identifier, a CVR-number, which is the official number given to a company when it is created. The public and regulators use this number to identify each specific company. Furthermore, a unique 'enhedsnummer' (unit number) is also provided for each company. This number originates from the index number used in the CVR register's ElasticSearch database, and is used throughout the dataset to link a company to its key variables. Similarly, an 'enhedsnummer' exist for each person registered in the data. This personal index number can be translated by Statistics Denmark to match their register data.

Since the focus of our study is on individuals associated with publicly traded companies, these had to be identified. We used the attribute called "børsnoteret" (listed) to identify publicly traded companies. Upon closer research, however, some of these companies were not, and had never been, listed on the Copenhagen (or any) Stock Exchange. Since the companies manually submit their data to the CVR register, data errors are to be expected. We argue that this is not a significant issue, since this information later is matched with the stock prices for these companies. Therefore, if a company mistakenly is registered as 'listed' it simply will not have any price information to merge with, and will therefore not be present in the data.

To identify the individuals connected to the listed companies, we used information on professional relations in the dataset. We identify potential insiders as people who are associated via auditing, the board of directors or executive management. The period of professional association is also stored. Finally, we create a variable for the number of unique companies an individual is associated with over the span of this dataset, which will be used as a control variable.

SKAT

SKAT is the Danish tax authority, and therefore stores vast information for the population of Denmark: when buying stocks or securities, an individual's bank is by law obligated to report these purchases to SKAT. When selling stocks, individuals must report this to SKAT for tax purposes (SKAT, 2018). This means that SKAT is an ideal source for obtaining real time trading data for the Danish population.

The trading data was acquired by our supervisor, Steffen Andersen. It contains information of the trades made by everyone living in Denmark between January 2nd 2012 and December 30th 2016, covering nearly five full years. For each trade there is a unique index number for the person trading. This number can be translated by Statistics Denmark to match their register data. A 'correction' code is included, which will indicate if there has been an error in the registration of a trade. Further variables include the ISIN code of the financial instrument traded, its name, and how many stocks/securities were bought or sold. Additionally, there is information on the country of origin for the traded paper, its currency, the exchange rate at the time of the trade, and whether the trade was a buy or a sell. Finally, the size of the trade, in DKK and in the currency of the country of origin, is also available in the data. As the purpose of our study is to analyse trading by insiders in Danish companies we disregard companies that are not listed on the Copenhagen Stock Exchange. This also simplifies the analysis significantly, since there will not be any issues with currency conversion. Furthermore, in our thesis we focus on stock trades, meaning that the trades of bonds, derivatives, and any other financial assets are ignored.

The correction code means that if there is a registration error in the dataset one trade will appear as three observations: one with the erroneous information, another with the adjusting information, such that the aggregation of these two observations give the status quo. The final observation then contains the correct information. From the correction code it is clear to see what observation is the adjusting one, giving the 'opposite' information. However, it is not clear, which one of the two other observations contains the original but false information, and which one contains the true information. In order to easily overcome this, and to have it as one trade, we aggregate the three different observations for such incidents. Since the correcting observation and the incorrect observation cancel each other out, the result of aggregating all three observations is the correct trade. Three observations are thus reduced to one, correct, observation.

Later in our study we link the trading information to price data from Datastream. This price data is at a daily frequency; trading activity and returns can therefore only be analysed at day-level. We argue that if insiders decide to trade on superior knowledge acquired via the company, this will not be markedly affected by the price fluctuations throughout a day. We therefore believe that aggregating trades to a day level will not result in any loss of valuable information. Thus the trade value, together with the number of stocks a person trades in a given company on a given day is aggregated. The distinction between buys and sells is naturally still maintained in this aggregated dataset. Analysing these aggregated trades there are still some outliers that look like errors that have not been correctly addressed by the correction codes. Some trade values are negative, and some also have the amount of stocks listed as negative. Since these errors are a small fraction of the entire dataset, we disregard them by restricting the total trade value and number of stocks to be nonnegative. The errors constitute a similar fraction of total trades for insiders and non-insiders, thus doing so should not bias any estimates.

The final structure of this dataset is as follows: the variables included are the person identifier, the ISIN-number of the company, the day of the trade, whether the trade is a buy or a sell, and how large this trade was in DKK. The total trade value is restricted to be nonnegative.

The Danish Financial Supervisory Authority

Among the many responsibilities of the Danish Financial Supervisory Authority (FSA), one is to monitor the Danish listed companies, ensuring that they comply with the regulation regarding insider- and other relevant information (The Danish Financial Supervisory Authority, 2018). In order to do so, the Danish FSA investigates the trading activity of both reported and unreported insider trades, together with corporate announcements that contain information regarding Danish listed companies. The Danish FSA therefore has a file containing all announcements that the Danish listed companies are legally required to report. We were able to obtain this information, with the help of Frederik Ole Lund-Thomsen, principal at the Danish FSA.

The file obtained contains information on announcements regarding Danish listed companies for the past 10 years, totalling 87,772 observations. Because of sensitive information at a personal level we were not allowed to receive information regarding changes of large equity holders and who has short positions in which companies in Denmark. Other than that, this announcement file is identical to what the Danish FSA uses in their screening of company announcements, thus aiding them in deciding which trades should be investigated for insider trading. For each announcement, the date of its publication is supplied. Furthermore, the announcement's headline, the name of the company in question, and its CVR-number is given. Finally, there is information regarding the nature of the headline, the number of attachments associated with the headline, and the language of the headline.

In order to get an overview of the announcement data, we investigated which companies had the largest number of announcements. The result of this was interesting in one specific case: for 655 observations in this dataset, the CVR-number was incorrectly specified as that for the Copenhagen Stock Exchange instead of the company in question. This error is likely due to the fact that the announcer of the headline was the Copenhagen Stock Exchange, and not the company itself. However, such announcements should be correctly linked to the company in question in order to get the most precise and correct analysis. To do so, we used the fact that the company name was in the headline. Using the CVR register, it was possible to link the company name to its correct CVR-number.

The announcement file had to be sent to Statistics Denmark. At Statistics Denmark, any personal or company-specific information is anonymised. The only company-specific information that could be used from this file is the company CVR-number, as this would be matched with an anonymous company identifier on Statistics Denmark's server. Both the company name and 'nickname' therefore had to be dropped as variables. Furthermore, since almost all headlines contained the company name, this variable also had to be deleted before sending the data off to Statistics Denmark. Therefore, in order to still contain some information from the headlines, we created several new variables. Several 'buzzwords' were identified and added as dummies if they were present in the headline. For the list of 'buzzwords' please refer to **appendix 1**. We argue that headlines containing words such as "share repurchase", "extraordinary general assembly", or "order" are more likely to be informative than headlines without such words. We therefore exclude headlines where none of the aforementioned 'buzzwords' are featured, leaving us with a total of 40,592 announcement observations. Naturally, this will be an imperfect selection of important announcements, but we believe that it will weed out the worst of the noise, without being too restrictive.

The final structure of the announcement data is thus as follows: for each observation its publication date is kept, together with the CVR of the company. Finally, the dummies for the buzzwords in the headline, as explained in the previous paragraph, are included.

Datastream

Thomas Reuters Datastream is a database, which among other things provides current and historical information for stocks prices. We used Datastream to obtain historical adjusted daily closing prices for all stocks on the Copenhagen Stock Exchange for the past 10 years. The purpose of using this data is to be able to examine the returns of the trades from the SKAT data. This data is very simple, required no real cleaning and thus requires little explanation. Downloading this data resulted in 220 unique ISIN-numbers.

In order to be able to classify traders as 'insiders', a link between the CVR-number of a company and the ISIN of its stock needed to be established. We have no knowledge of any database where this is available, nor did extensive research reveal one such source. Therefore, this link had to be manually established. For each of the 220 ISIN-numbers, a Google search revealed the company and thus also the CVR-number associated with this ISIN. Lacking an official source for the ISIN and CVR link, we believe that this was the only and optimal solution. To check for validity, these CVR-numbers were compared to the CVR-numbers for the listed companies in the data from the CVR register, and the biggest part matched perfectly. The ones that did not match were, as previously predicted, companies that are marked as listed in the data from CVR register but not in fact listed. Thus, they will per definition not have an ISIN-number. The structure of this dataset is, as above, very simple and contains two variables: ISIN and CVR-number. Each of the 220 ISIN-numbers is unique and links to one CVR-number only. Because a company may have several stocks listed, one CVR-number may link to several ISIN-numbers.

Statistics Denmark

Statistics Denmark is a governmental organisation responsible for creating statistics on the Danish society, often relying on public register data. On top of the provision of statistics, Statistics Denmark also allows researchers to buy access to some of their data. We have via the Head of Department of Finance at CBS, Morten Sørensen, and our employer, Steffen Andersen, been given access to a server at Statistics Denmark.

Every Dane is given a personal identification (CPR) number at birth. This number is used extensively: for opening a bank account, using your health insurance, getting government benefits, etc. A person's CPR-number can therefore be linked to his/her date of birth, current address, full set of names, CPR-numbers of both parents, whether the person is married or divorced, amount of children, education, and so on (CPR - Det Centrale Personregister, 2018). This information is available on Statistics Denmark's servers. The true CPR-number is not supplied. Instead, Statistics Denmark has generated a pseudo CPR-number, called a pnr (person number) for each individual. This pseudo CPR-number is unique for each person, and thus allows the researcher to unique identify subjects without ever seeing the true CPR-number. Likewise for companies, a pseudo CVR-number is created by Statistics Denmark. Companies can thus be linked, while still remaining unidentifiable and thus anonymous from the researcher's point of view.

The data files on the Statistics Denmark server used in our study are as follows:

- BEF: personal data, containing a pnr for each person, their age, date of birth, gender, marital status, when the marital status is valid from, pnr for any potential spouse, a code to uniquely identify a family/household, and the pnrs for both mother and father (Statistics Denmark, 2018).
- IND: individual income data, containing a pnr for each person, amount of money in the bank account, the individual's wealth, mortgage deeds, and more (Statistics Denmark, 2018).
- UDDA: individual education data, containing a pnr for each person, the highest level of completed education by the individual, a unique identification number for the institution, and the source of the education data (Statistics Denmark, 2018).
- AKM: individual employment data regarding the field of work of the individual, for example whether the individual works as (top) management (Statistics Denmark, 2018).
- IDAP: individual employment data regarding whether the individual is unemployed, employed, self-employed, retired or out of the workforce (Statistics Denmark, 2018).

Furthermore, we accessed a file, already on the server, linking the education code to two variables: "fsp1e", which facilitates classifying what type of education or work, the education code refers to (Statistics Denmark, 2018) and "pria", which states the minimum amount of months of education needed to complete each type education (Statistics Denmark, 2018). We were privileged to get this document thanks to Julie Marx, PhD student at the Department of Finance at CBS, who provided the file. By combining this file with the file with education data, we linked the highest completed education for an individual with how many years it as a minimum took to complete said education, and whether the education gives you financial literacy[3].

[3] Financial literacy here is defined as graduated or trained in finance or economics. This includes individuals having completing a bachelor's or master's degree within finance or economics, such as Polit, Oecon, mathematics and economics,

In order to get one file containing all the information about individuals, these six files had to be merged to obtain personal characteristics for each of the years 2012 to 2016. The result of this merge is therefore five large yearly files, each containing an extensive amount of information about each individual. We use these files later in our study to control for personal and socioeconomic characteristics. Since the individual employment data regarding employment and unemployment is only available until 2013, this will be assumed constant for the years after 2013. This is naturally an imperfect assumption, but it is the only way to get some employment data for those years. From BEF, each person's area of residence, gender, age and marital status was kept. Furthermore, because this dataset contains a unique family identifier, and the pnrs for individuals' parents, we were also able to establish the size of a household and the number of children for each individual. From IND, the total personal income (excluding estimated rental value of own residence, before any deductions of interest expenses), the individual's mortgage and individual's wealth (defined as their net residual assets excluding any assets from pensions) were kept as variables. From the combination of UDDA and the file from Julie Marx, we kept the length of education in years and whether the education of the individual resulted in financial literacy. From AKM we stored whether an individual is employed in management, top-management or works with finance. Finally, from IDAP we kept the individual's employment status.

In addition to this, the five datasets[4] mentioned in the beginning of this section were sent to Statistics Denmark, thanks to our supervisor and employer, Steffen Andersen. Individuals are uniquely identified in both the trading data and the CVR register data. Statistics Denmark can replace the ids provided in these datasets with the anonymised pnr used to identify individuals in their datasets. Similarly, the company CVR-numbers from the CVR register data, the announcement data, and the link between CVR and ISIN-numbers are also anonymised on the Statistics Denmark server, such that a pseudo CVR-number is used. Finally, ISIN is not anonymised and therefore remains the same in the trading data from SKAT, the daily price data, and the link between CVR and ISIN.

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actuary and agronomy, having completed a PhD within finance or economics, and individuals who have been bank educated.

[4] The five datasets are as follows: individuals associated with Danish listed companies from the CVR register, trading data from SKAT, announcement data from the Danish FSA, daily price data, and the link between ISIN and CVR-numbers from Datastream.

The Assembling and Structuring of the Main Datasets

We examine trading by insiders by looking at it in two different ways: through an event study and a pooled cross-sectional regression. The data is structured in two different ways: firstly by linking each announcement for a company to all trades in the same company, and secondly by linking each trade in a company to all announcements regarding said company. The distinction here is that in the former file the same trade can appear several times, as it will most likely be related to several announcements. This file is later used to create an event study, analysing the trading activity in a company before and after an announcement. In the latter file, however, each trade is only observed once, and the amount of announcements regarding the trading company, in windows both before and after the trade, are summed. This file is used to create a pooled cross-sectional regression, relating the trade amount to: several personal characteristics, whether the person is an insider or not, whether the person is somehow related to an insider, and the number of announcements before and after said trade. Furthermore, returns are analysed for each of the groups of traders. This section will continue as follows: to start off, the main assembly of the data on the Statistics Denmark server is explained. This main assembly is the first step in creating the two different files for analysis. Following this, we detail the assembly and structure of first the event study data, and then the regression data. We highlight any potential issues with the data structure or the data assembly along the way. Finally, summary statistics will be provided.

The Main Assembly of the Dataset

To facilitate structuring the data, the trading file from SKAT is split into several smaller files by year of trade. This results in five files, from 2012 to 2016. In the following subsection we explain how our main dataset was created. Firstly, for each of these years the ISIN and pseudo CVR link is merged on. This means that it is possible to match a stock trade to the company that issued the stock. Secondly, the CVR register data is merged on each year, enabling us to identify which trades constitute trades of insiders. Together with this, our definition of what constitutes an insider trader in our dataset is provided. Furthermore, we identify traders who are related to corporate insiders through family or professional ties. Thirdly, each trade in a company is linked to all the announcements relevant for this company, allowing us to investigate the trading patterns both by insiders and non-insiders, and how this can be related to the company specific announcements. Finally, we discuss any benefits and problems with the assembled dataset.

Merging with the Pseudo CVR and ISIN Link

To start off, we match the ISINs from the trading file with the pseudo CVR-number for the company that issued the stock, dropping the trades with ISINs that could not be matched. These account for 3,924,777 out of 15,296,352 observations, or just under 26% of the observations over the five years. We investigate the ISINs that could not be merged: for the biggest part, 3,192,622 observations, this is simply because the stocks are traded in other countries than in Denmark, and thus cannot be matched using the pseudo CVR and ISIN link. Since the focus of our study is on companies listed on the Copenhagen Stock Exchange, dropping these observations is not a major concern. Furthermore, for 1,683 observations there was no ISIN code, and thus could not be linked to any company. For the remaining 730,472 trading observations that were not merged, the following explanations can be found: they are rights, bonds, companies going through bankruptcy (with observations in 2012 even though the company was declared bankrupt in 2011), or the ISINs are listed on other stock exchanges although the country code was stated as Danish.

Classifying Traders and Merging With the CVR Register Data

The files with the trading information linked to the pseudo CVR are then merged with the CVR register data. Here, the observations are matched using the pnrs (unique personal identifiers) provided by Statistics Denmark. For each observation the pnr is matched with the observations for the individual from the CVR register data. We define corporate insiders as individuals *who have carried out a trade in a given company while associated with the same company*[5] (either via auditing, the board of directors, or executive management). Thus, if a person is associated with the company that she trades in *and* the trade is carried out during this period of association, this will constitute an insider trade.

Two further definitions of traders will be used throughout this paper:

- In listed company: this will be used to describe individuals who are associated with *a* company but either trade in another company or trade in the company, but outside his/her period of association. Thus this will be the entire list of people from the CVR register data, minus the ones classified as insiders.

[5] This means that the "start date of association with the company" <= "date of the trade" <= "end date of the association with the company"

- Presumed outsider: anyone who is not associated to any company via the data from the CVR register. We have chosen to call them *presumed* outsiders since the data from the CVR register may not be perfectly informative regarding all insiders or people who have superior information regarding companies.

Because of the above definitions, the same individual can both be an insider and an individual in listed company. Say, if Mr Smith is in the board of company A between the 1st February 2012 and 3rd April 2015, any trades by him in this period in company A will classify him as an insider. If he also trades in company B (or any other company) this will classify him as "in listed company".

Furthermore, the CVR register is used to identify potential insiders through network analysis. This will be used to investigate whether individuals who are associated to companies via their network trade differently from the rest of the population, and whether they profit from this. The two networks to be investigated are ties from family and the professional network.

To investigate the family ties, the population data from Statistics Denmark is linked to the individuals from the CVR register data. From this, we identify parents, children and spouses of the traders. If a trader is related to an insider or person in a listed company in this way, he/she is identified as a family trader. If this individual trades in the same company that their relative is associated to, *while* the relative is associated with said company, the individual is classified as an insider family trader. This will allow us to examine whether an individual trades differently if she is related to someone who is associated with a listed company.

To investigate the professional network, each individual affiliated with a company is matched with all others in the same company during the same period. The same individual is then linked to all other companies he/she is related to, and the period for which such an affiliation takes place. This provides us with professional links: if Mr Smith from earlier is a board member in both companies A and B, and Mrs Johnson is a board member only in company B, Mrs Johnson will now also be linked to company A via her connection, Mr Smith. Insider company network traders are thus defined as individuals who trade in the specific company they are related to via this network during this period of association. Thus, Mrs Johnson would be classified as an insider company network trader if she traded in company A while active in company B, *and* while Mr Smith was active in both companies A and B.

A natural extension to this network analysis, but unfortunately beyond both the time frame and scope of our master's thesis, would be to look at links further out, such as uncles, cousins, nieces, grandparents, grandchildren, spouses' relatives, school ties, and further professional links.

Merging with Price Data and Calculating Returns

To be able to make consistency checks later, we use the price data to generate both absolute and abnormal returns for the traded stocks. For each ISIN, for each date, returns are calculated from 1 to 30 days.

Absolute return for stock i is calculated using the closing price of the day of the trade ($P_{i,t}$) compared to the stock price over the subsequent n days ($P_{i,t+n}$):

$$r_{i,t+n} = \frac{P_{i,t+n} - P_{i,t}}{P_{i,t}}$$

To construct abnormal returns, we first generate a market return by using the OMX20 as a proxy for the market. For each stock, a market beta is calculated by regressing its return on the assumed market return:

$$\beta_i = \frac{Cov(r_t^{market}, r_{i,t}^{realised})}{Var(r_t^{market})}$$

The risk free rate is assumed to be zero, as the Danish National Bank's interest rate (foliorente) has been zero from 1st June 2012 (Danmarks Nationalbank, 2018). Furthermore, both the 1-month LIBOR rate based on Euro and the 3-month treasury yield have been zero, or remarkably close to zero, over the period investigated (Federal Reserve Bank of St. Louis, 2018a) (Federal Reserve Bank of St. Louis, 2018b). Both rates often serve as the main proxy for the risk free rate (EY, 2015) (Hull & White, 2013). Additionally, to check for consistency, a risk free rate of 1% was also investigated, which gave virtually identical results[6]. With the risk free rate defined and the market betas for each stock, expected returns are calculated:

$$r_{i,t}^{expected} = r_t^{risk\ free} + \beta_i(r_t^{market} - r_t^{risk\ free})$$

[6] The results of the average abnormal returns using a 0% and 1% risk-free rate can be found in **appendix 19** and **appendix 20** respectively

Abnormal returns are created as the difference between the realised and expected return of the stock.

$$r_{i,t}^{abnormal} = r_{i,t}^{realised} - r_{i,t}^{expected}$$

Finally, to make the results more intuitive we annualise the returns using compounding:

$$r_{i,t}^{annualised} = \left(1 + r_{i,t}\right)^{\left(\frac{250}{t}\right)} - 1$$

Where 250 is the amount of trading days in a year and t is the holding period in days the return is calculated from. Using compounding assumes that one continuously invest at that rate over the year.

This information is then merged with the large data file, which thus provides information regarding the returns for each trade.

Merging with the Announcement Data

Finally, the abovementioned files are matched with the announcement data. Each pseudo CVR-number in the trading/CVR register data is matched with all the announcements from the announcement file regarding that pseudo CVR-number. A company/ISIN without any announcements will therefore not be present in any of these files. This matching process results in some immense files for the years 2012 through 2016. These five yearly datasets are the ones used in creating the event study and the regression files.

Discussion of the Large Dataset

In this part we highlight the potential issues with and the strengths of this dataset. A potential issue is the limited time span of the trades, ranging from 2012 to 2016. In general, the larger the amount of observations, the more robust the result, and therefore more years of trading data would be desirable. Further research could include testing if our conclusions hold for an extended trading dataset. However, for the purpose of our study, the five years of data are deemed to be sufficient to produce interesting results, as there are roughly 10 million observed trades in the dataset.

An additional issue may be the identification of insiders. In the US, all trades by corporate insiders have to be reported to the SEC. A dataset with such information would contain a more correct specification of who, in the trading dataset, in fact are insider traders. As mentioned earlier, we used people trading in the company they are affiliated to at the time of trade to determine insider traders. This definition is indeed incredibly similar to what the SEC defines as insider trading (SEC, 2018), meaning that this should not constitute a significant problem.

One of the main strengths of our dataset is the vastness of information it contains, and thereby its full sample properties. For the five observed years, the data contains *all* the trades in these companies by individuals living in Denmark, which indeed is unique. This also means that we can compare the trades made by insiders to the trades made by the general population of Danish traders.

Furthermore, although our announcements have been crudely selected, these announcements are exactly the ones used by regulators in Denmark. This firstly adds credibility to the argument that our announcements are relevant for examining insider trading. Additionally, this means that the Danish FSA should be able reach similar conclusions as our master's thesis.

The Event Study File

In order to make the five yearly datasets more manageable, we drop any observation where the trade carried out is not between 180 calendar days before and 30 calendar days after an announcement. This means that we will not be able to conclude anything on whether or not insiders trade earlier than six calendar months before an announcement. Some literature does indeed find that insiders trade as early as six months prior to announcements (Ke et al., 2003). However, research (Jeng et al., 2003; Watson & Young, 1999) also shows that insiders trade in the short run. Additionally, due to the crude selection of announcements, we do not believe that any significant insider trading patterns that long before an announcement will be detectable in our dataset.

Furthermore, the calendar days were translated into business days, excluding all weekends, meaning that the day after Friday is assumed to be Monday rather than Saturday. Translating the calendar days into days of business results in the trades in the dataset being in the range of 129 business days before to 21 business days after an announcement. The reason for doing so is that the results obtained are more consistent, as the market is not open for trading during the weekends. Some announcements are dropped because of this, since information can be published in weekends, however, this turns out to be an insignificant proportion of all announcements[7]. One caveat, however, is that this translation was only done on weekends. This means that any other holiday, such as the 1st January, will not be omitted if it happened to fall on a weekday. This is naturally not ideal, since these should have been omitted. For future research we therefore suggest a more thorough selection of dates, excluding all non-trading days from the dataset. However, since the weekends are excluded, and holiday days during the week are small subset of the total amount of weekdays, we argue that the results and analysis will still be valid and relevant.

Finally, these five yearly datasets that were split up by year, were merged into one large dataset for the event study, thus containing trades for all of the years from 2012 to 2016. From here, the variables are sorted on announcements, and not on trades. This is done in order to be able to analyse how trading behaves leading up to and following announcements. It is worth stressing once more, that in this dataset each trade is linked to *all* announcements that fit in the aforementioned time window. This means that each trade may very well be in the dataset several times, especially if the trade is made in a company for which there are many announcements. What we want to analyse in this event study is how the pattern of trade behaves before and after an announcement, both for insiders, people in listed companies, and presumed outsiders.

Setting Up the Regression File

As when creating the event study, in order to make the five yearly datasets more manageable, we restrict the announcements to certain time windows. Here, however, the individual announcements are not kept, but rather aggregated over trades. For each trade, the number of announcements for 30 days before is summed. This allows for the creation of a dummy variable that specifies whether there will occur an announcement within 30 days of the trade. Additionally, a dummy, that is one if the trade is carried out on the day of an announcement, is created. After doing so, the specific announcements and their respective dates are dropped. This does result in a loss of information, but also means that each trade is only observed once in the dataset. The advantage of doing so is that it becomes possible to analyse how individuals trade in general, and to see how different kinds of insiders and outsiders trade around announcements.

[7] Announcements observations in weekends turn out to be less than 1% of the total data

Following this, for each year, the relevant personal characteristics from Statistics Denmark are merged on. This allows for some interesting descriptive analysis of who the average trader in Denmark is, and how insiders and people in listed companies do or do not differ from these. For roughly 7% of the trades, there were no person characteristics to merge on. Of these, for 15% it was possible to find a match with that person's characteristics from another year. These variables were assumed to be constant over time in all but one case: the individual's age was corrected by the difference between the year in question and the year the characteristics data was from. The people that could not be merged are naturally of a concern. We argue that some of these cases will be foreigners who trade in Denmark and therefore cannot be found in the Statistics Denmark database. Another explanation could be that they were not correctly specified/identified in some of the personal characteristics data from Statistics Denmark. It is not exactly clear which is the most correct conclusion, but we argue that it should not bias the results of the findings, since there has been no selection in who were and were not merged on the dataset. The advantage of this merge is that it is now possible to relate trading activity both to being an insider or not and the individual's personal characteristics.

Finally the five years of data are merged into one. This pooled cross-sectional regression dataset now contains a comprehensive amount of information: for each trade, there is information regarding the specific trade, regarding whether the trader is associated to any company listed in Denmark, has family in or professional ties to a listed company, the personal characteristics of this individual trading, the returns of the stock price following this trade, and finally the amount of announcements regarding the company, before and after the trade. Over the five years there are a total of 7,737,506 observations. Here, one observation is defined as how much one person trades in one company, split into buys and sells, over the course of the day, as specified in the data section.

Summary Statistics

We now display some key summary statistics. These include characteristics of the different types of traders and comparisons between groups. Furthermore, we investigate the distribution of the trade values.

Table 1 summarises such characteristics and compares individuals directly associated with companies to outsiders across all sells. **Appendix 2** provides the full version of **table 1**. **Appendix 3** shows the same for all buys. In each table, columns 1, 2 and 3 describe the presumed outsiders, people in listed companies and insiders respectively. Columns 4, 5 and 6 provide the differences between presumed outsiders and people in listed companies, presumed outsiders and insiders, and individuals in listed companies and insiders respectively. For each of the differences, the level of statistical significance is also provided. Except for a few variables, all of the differences are statistically significant at the 99% level, which indicates that the three different types of traders indeed are different.

Table 1 shows that both insiders and individuals in listed companies are less likely to be female than the average trader. Furthermore, perhaps surprisingly, people in listed companies are on average older, whereas there is no significant difference between the age of presumed outsiders and insiders. An average age of around 50 additionally shows that the traders are older than the general population. Furthermore, in the sample, the insiders and individuals in listed companies are the ones with the longest education by far, which does not come as much of a surprise, since it is reasonable to expect companies to hire the most qualified people to sit in boards etc. of listed companies. It is worth noting that the insiders are more likely to have financial literacy, as defined earlier in this section, which presumably must be an advantage when wanting a position high up in a company. Also, insiders and individuals in listed companies have a much greater probability of being self-employed than the average trader. In addition to this, insiders are much more likely to be working within finance, as management or top management, which once more seems consistent with who one would expect to be insiders and/or to be related to listed companies.

The differences in education length, education type, and job type for the three types of traders translate into a difference in income. Both when looking at individual income and wealth, the presumed outsiders are by far the "worst" off. Furthermore, both the insiders and the individuals in listed companies trade for significantly more than the presumed outsiders on average – both when looking at trade level, company level and on an annual basis. Regarding trade size as a percentage of income, none of these are statistically significant. From the table it is also evident that the insiders are a small fraction of the total population of traders, as one would expect.

We thus observe that the three types of traders have significantly different characteristics: therefore, it is important to control for these characteristics when analysing their respective trading patterns. In the regression study we will control for exactly that.

Table 1: Personal Characteristics for Insiders for All Sells

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider	in listed	insider	(2) – (1)	(3) – (1)	(3) – (2)
female	0.38	0.11	0.14	-0.27***	-0.25***	0.02
age	53.42	59.41	51.56	5.99***	-1.91	-7.86***
couple	0.67	0.86	0.89	0.19***	0.22***	0.04
number of children	1.51	2	2.11	0.49***	0.59***	0.11
education length	14.06	15.54	16.2	1.49***	2.13***	0.66***
financial literacy	0.08	0.31	0.4	0.23***	0.32***	0.09**
unemployed	0.02	0.01	0	-0.01***	-0.02*	-0.01
self-employed	0.05	0.26	0.5	0.22***	0.45***	0.24***
works within finance	0.02	0.06	0.09	0.03***	0.07***	0.04*
works within management	0.04	0.24	0.46	0.20***	0.42***	0.22***
works within top management	0.01	0.15	0.3	0.14***	0.28***	0.14***
individual income	428061.5	2740000	5480000	2.31e+06***	5.03e+06***	2.73e+06*
annual trade as percentage of income	2.1	5.23	1.76	3.12	-0.37	-3.47
individual wealth	1170000	14000000	10400000	1.28e+07***	9.17e+06***	-3.59E+06
average trade size	51070.48	554219	9340000	503148.55***	9.29e+06***	8.79e+06***
average trade in company per year	111707.6	1050000	11300000	942149.49***	1.12e+07***	1.03e+07***
average trade amount per year	284442.8	2140000	13400000	1.86e+06***	1.31e+07***	1.13e+07***
Observations	498754	3371	232	502125	502125	3603

* p<0.05 ** p<0.01 *** p<0.001

Appendices 4 through **7** provide similar tables for the family and professional network of individuals associated with listed companies. What is worth noting is that the socioeconomic factors for the family trading groups resemble the average trader more than the average insider.

Furthermore, we also investigate the trade value variable, which is used as the dependent variable in the regression. For standard OLS regressions it is desirable that the dependent variable approximates a normal distribution. As shown in **figure 1**, the total trade value is nowhere near normal. However, the log of the trading value looks much more like a normal distribution, as can be seen in **figure 2**. Therefore we will use the log of the trading value in our regressions.

Figure 1: Trade value (DKK) histogram

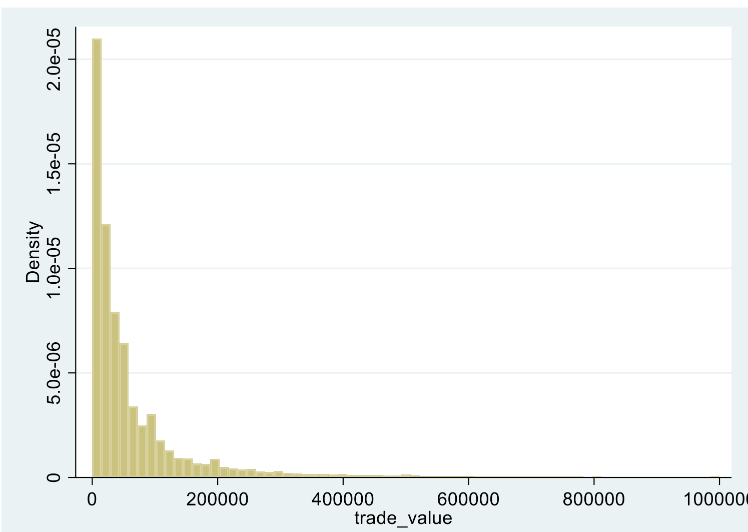
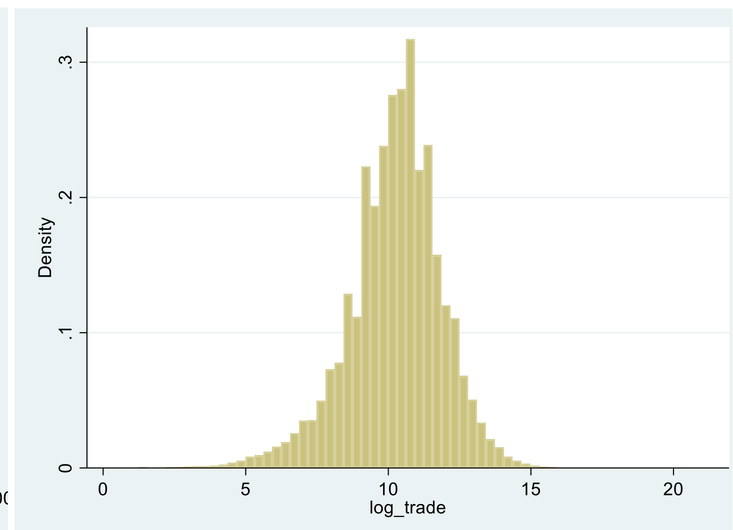


Figure 2: Log trade value histogram



Method

This section covers the methods used for the three different types of analysis shown in this study: the event methodology, the regression methodology, and how we examine the returns.

Event Study

Initially, we examine the aggregate trading pattern for direct insiders, individuals in listed companies, and presumed outsiders around company announcements. We use an event study approach, where the advantage is the provision of a graphical and intuitive analysis of trading patterns. The event study thus allows for an easy comparison between the different categorical groups of traders. We first describe our two hypotheses regarding trading behaviour of individuals, and explain how these would show up in an event study. Then, we go through the event study methodology. Finally, we discuss the relative strengths and weaknesses of this event study.

The purpose of the event study is to investigate hypotheses 1 and 2:

H1: *"Insiders' trading activity rises prior to the release of corporate announcements."*

H2: "*Corporate insiders are better at predicting the direction of a significant announcement than outsiders."*

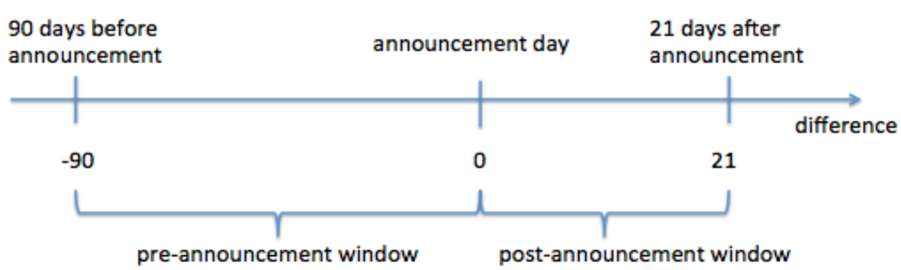
The nature of these hypotheses is to examine the trading patterns of corporate insiders vis-á-vis other categorical groups of traders. If hypothesis 1 holds one would expect to see increased trading activity for corporate insiders before corporate announcements while other (non-informed) trading groups would exhibit no such pattern. However, finding evidence for hypothesis 1 is not sufficient to conclude that insiders have superior knowledge, as one cannot infer whether they trade in the right direction. Hypothesis 2 predicts that corporate insiders are better at predicting the outcome of a future announcement that moves the stock price. If this indeed is the case, one should find a systematic difference in the direction of trading before significant announcements by corporate insiders, while no such pattern is to be expected for other traders. Finding evidence on potential exploitation of non-public information for profit reasons hinges on neither of the hypotheses being rejected.

Event Study Methodology to Answer Hypothesis 1

The event study methodology has been used on financial data since 1933 (MacKinlay, 1997). Event studies allow researchers to study the daily development of economic variables, such as firm value, around value changing events (ibid). The period of measurement (the event window) is both at the event date but also prior to and post the event. Event studies thus serve as a strong tool to measure economic developments post and prior to events (ibid). For our study the variable of interest is the development of the trading volume of insider traders prior to company announcements. If corporate insiders trade more than usual prior to corporate announcements it suggests that they trade using non-public information. As a result, we argue that using an event study is a strong methodological tool to study pre-announcement trading, as an event study allows for measurement of trading activity on each day prior to corporate announcements. Scholars such as Lorie & Niederhoffer (1968), Meulbroek, (1992), and Watson & Young, (1999) use methodologies similar to the event study method to investigate insider trading activity prior to corporate announcements. Furthermore, Harris & Gurel (1986), Chen, Wang, & Chen (2011), and Wong (2002) have used event studies to measure trading volume development prior to corporate announcements. These authors have studied different variations of the average abnormal deviations from daily trading volumes using total trading volumes on stocks. The abnormal trading volumes are calculated with respect to the trading volume of the market. We are highly inspired by the use of daily trading deviations from the average trading volume for our study. However, since we study the trading volumes of different categorical groups and therefore not the entire trading volume of the stock, using CAPM style regressions to obtain abnormal deviations is unfeasible, as some categorical groups such as insiders and "in listed company" trade infrequently. Therefore, one risks biasing the CAPM style trading volume coefficients. This is also an issue in the returns literature on infrequently traded assets (Ang, 2011), (Pedersen, 2015), and (Korteweg & Sorensen, 2007). We thus study a simpler unit of measurement: daily deviations from average trading volume to avoid bias. Future research should, however, investigate the methods used by previous scholarship.

In the event study we analyse trading activity in a window around corporate announcements. To do so, we create a new variable, which is the number of business days between the day of the announcement and the trading day. This variable will henceforth simply be referred to as the "difference". Thus, for trades carried out before an announcement this figure will be negative, while it will be positive for trades carried out after the announcement. For trades executed on the day of the announcement this variable will be zero. This is illustrated in **figure 3**.

Figure 3: illustration of "difference"



Similar to past literature we use trading volume as a proxy for trading activity (Chen et al., 2011; Harris & Gurel, 1986; Wong, 2002). However, due to the fact that trading volume of each stock is split up into three different categorical groups in our dataset we had to design our own deviation measures. To be able to analyse how the trading activity changes around announcements, we compute the daily deviation from the average daily trading volume. We compute the deviation of average trading volume for the three different types of traders (insiders, in listed company, and outsiders) in two ways: the first is done using equal-weights, while the second is value-weighted. The value-weighted approach is similar to computing a simple average for a variable, as we calculate the aggregated trading volume divided by the average trading volume for each categorical group. This measure is simple, but highly useful, as companies with large trading volumes are given a larger weight compared to small companies. We believe this measurement is relevant, as one would expect large trading volumes to be indicative of unusual trading patterns. This also allows for the analysis of insider trading on market level. Furthermore, the value-based method is useful as it is not biased by small companies with infrequent trading activity.

In comparison our equal-weighted trading deviation measure is first calculated on company level for each categorical group, the average on societal level is then computed. By using equal weights one thus assigns the same importance to large and small companies, irrespective of the trading volume of the different categorical groups. This analysis is useful for examining whether insider trading is prevalent in small companies that would otherwise have been ignored using the value-weighted approach. Prior to analysing the data we were not able to conclude which of the two measurements were most precise. As a result, we decided to include both measurements in our analysis, as they reveal whether insider trading patterns are more pronounced for large or small trading volumes.

To investigate which trading deviations are statistically significant we include a simple t-test. The t-statistic is defined as:

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}}$$

Where $\bar{x}$ is the sample mean, μ is the population mean, s is the sample standard deviation, and n is the size of the sample. The test is used to investigate whether the average relative trade for selected intervals is significantly different from the predicted relative trading volume for each group. The null hypothesis is that the relative trading volume is equal to 1, which is the average daily trading deviation.

Equal-Weighted Relative Trading Volume

The equal-weighted relative trading volume measures the average of the daily deviations from the average trading volume on company level, for each of the different types of traders. To construct this measure, one must first construct the relative trading volume for each of the companies, and then take the average of this. Dividing the daily aggregated trading volume by the daily average over the period creates the relative trading volume on company level. The steps used to generate the equal-weighted relative trading volume are listed below:

The total trade volume (TV) in DKK is first calculated for each "difference", j, for each company, i, for each of the three types of traders, c. For each of the types of traders, the total trade volume is summed over the total amount of individuals of that type, N:

$$TV_{i,c,j}^{equal} = \sum_{n=1}^{n=N} TV_{i,c,j,n}^{equal}$$

The average trading volume (ATV) in each company, i, for each of those types, c, over the whole sample period (from $j = -129$ to $j = 21$) is then calculated:

$$ATV_{i,c}^{equal} = \frac{1}{J} \sum_{j=-129}^{j=21} TV_{i,c,j}^{equal}$$

The ATV is then used to estimate the relative total trading volume (RTV) made in each company, i, for each "difference", j, and for each type of trader, c, compared to an average day[8]:

$$RTV_{i,c,j}^{equal} = \frac{TV_{i,c,j}^{equal}}{ATV_{i,c}^{equal}}$$

[8] Thus, if the average trading volume in a company over the whole period is 10 DKK per day, and the amount traded in that company on a particular day/"difference" is 20 DKK, this variable will be equal to 2.

The RTV is thus the daily trading volume deviation from the daily average on company level. Finally, these RTVs on company level are averaged across the I companies in the sample. This means that for each day, j, an average relative trading volume $(ARTV)$ is estimated for each type of trader, c:

$$ARTV_{c,j}^{equal} = \frac{1}{I}\sum_{i=1}^{i=I} RTV_{i,c,j}^{equal}$$

This thus gives an equal-weighted estimate of the relative trading, where companies with small and large total trading volumes are given the same relative weight in the calculation of how the relative trading volume changes before and after an announcement. Since these figures are relative amounts, an ARTV of 1 implies that the trading volume on the day of measurement was equal to the daily average over the entire estimation period.

Value-Weighted Relative Trading Volume

The value-weighted relative trading volume measures the *total* daily deviation from the average daily trading volume. This aggregation method means that companies are *not* given equal weights; instead the largest trading volumes are weighted more. To construct this measure one must simply divide the daily trading volume on the aggregate level by the average daily trading volume. The steps used to generate the value-weighted trading volume are as listed below:

The total trade volume is first summed for each day in the event study window "difference", j, for each type of trader, c, disregarding the company identifier. Once more, for each of the types of traders, the total trade volume is summed over the total amount of individuals of that type, N:

$$TV_{c,j}^{value} = \sum_{n=1}^{n=N} TV_{c,j,n}^{value}$$

TV thus measures the total trading volume per day in the event window per trading group. Following this, the average trading volume per day for each of the types of traders, c, over the whole sample period (from $j = -129$ to $j = 21$) is calculated:

$$ATV_c^{value} = \frac{1}{J}\sum_{j=-129}^{j=21} TV_{c,j}^{value}$$

Finally, to get the relative trading volume (RTV) for each "difference", j, for each type of trader, c, the total trade volume (TV) is simply divided by the average daily trading volume (ATV):

$$RTV_{c,j}^{value} = \frac{TV_{c,j}^{value}}{ATV_c^{value}}$$

This thus gives a value-weighted estimate of the relative trading, where larger trading volumes are weighted more than smaller trading volumes. As for the equal-weighted measure, a value of 1 for a "difference" will correspond with an "average" trading day.

Event Study Methodology Discussion Regarding Hypothesis 1

This event study will thus provide information regarding how trading activity of individuals behaves before, at, and after announcements for each of the different types of traders, and whether this behaviour differs between the types of traders, testing hypothesis 1. The advantage of these aggregation methods is that there should be no bias in the sampling: *all* trades are aggregated, and all companies are included.

Compared to MacKinlay (1997) and traditional event studies, the whole event window is used in the calculation of the average daily trading volumes and relative trading. Event studies looking at returns usually use an estimation window that does not overlap with the event window in order to calculate non-biased beta coefficients. As we do not calculate expected returns in relation to the event study, but instead want to compare trading deviations in the event window between the different groups of traders, we have used the entire sample to obtain the average daily trading volume for the different groups. This is a deviation from the literature, but seems justifiable given that we are consistent in comparing the different groups of traders. Furthermore, it will only result in our results being more conservative, which lends credibility to any findings.

As mentioned previously, the aggregation method is crude: information regarding how many people trade, the amount per person etc. is lost. Due to this, the conclusion will be expected to be crude as well, which is a weakness of this study. It is possible to analyse how the three different types trade, but there is no clear conclusion on whether any difference is due to the type of trader or whether it is simply due to differences in personal characteristics between the three types. The data section showed that there are significant differences in the characteristics of the three types of traders, thus the question of whether insiders, *all* else equal, trade differently from presumed outsiders, cannot be answered in the event study. In order to carry out analysis on characteristics we therefore look to the regression – here it will be possible to relate any differences in trading to both individual characteristics and being an insider.

Event Study Methodology to Test Hypothesis 2

Similar to Lorie & Niederhoffer (1968) and Cohen et al. (2012), we limit the event study dataset to only include significant corporate announcements. We define a significant corporate announcement as one resulting in an absolute price change of at least 5% on the day of the announcement. This allows for the testing of hypothesis 2 that postulates that pre-announcement insider trades are more likely to be in the direction of the announcement. Thus, we expect to see that insiders buy (sell) more before announcements resulting in positive (negative) price changes. No such pattern is expected for outsiders. Like Lorie & Niederhoffer (1968) we construct ratios in order to test whether the direction of trade predicts the price outcome of the announcement. Our ratio is the purchase ratio, which measures the number of purchases to purchases and sells. These are tested with a t-statistic to examine their statistical significance. The null hypothesis is that the amount of buys and sells are similar, giving a purchase ratio of 50%.

$$Purchase\ ratio = \frac{Purchases}{Purchases + \ sells}$$

$$t = \frac{Purchase\ ratio - \ 0.5}{\frac{s}{\sqrt{n}}}$$

If one finds that the pre-announcement purchase ratio is statistically different from 0.5 and matches the direction of the announcement, it may suggest that the group exploits non-public information.

Regression Study

In addition to the event study, we also link trading behaviour of individuals to both their personal characteristics and the type of trader they are. As shown in the data section, the three types of traders have significantly different characteristics. It would therefore not be unreasonable to argue that any difference found in trading activity in the event study is simply due to socioeconomic factors instead of having access to non-public information. Our study is, to our knowledge, the first investigation of pre-announcement insider trading patterns using register data to control for socioeconomic factors. As a result, we have decided to run a pooled cross-sectional regression to control for socioeconomic factors. The regression study will thus aid us in testing hypothesis 3:

H3: "*Differences in trading patterns are not explained by socioeconomic factors.*"

In order to investigate hypothesis 3 we therefore need to study the average effect on the trade size of a corporate insider when a future announcement is to be released within 30 days of the trade. In line with the event study we have chosen the monetary size (trade value) of each transaction as our dependent variable. As trade value is not normally distributed we use the log transformation to approximate a normal distribution. To measure the effect of the occurrence of an announcement on pre-announcement trade values we construct two categories of dummy variables: firstly, we construct n dummies, called $x_{n,i}$ in the regression equation below, that classify a trader into being an "insider", the family of a corporate insider, an individual employed in another listed company, and whether a person is linked to a corporate insider though their professional network. We construct the trading group identifier dummies such that the dummy equals one if a person is e.g. a corporate insider and trades in his associated company otherwise the dummy equals 0. The matching coefficient to the trading group dummies, β_n, displays the difference in trade size to the outsider group.

Secondly, we construct a time dummy, *30d*, which equals one if a company specific announcement is to be released 30 days within the time of the trade. If no company specific announcement occurs regarding the traded stock the dummy equals 0. The coefficient matching 30d, θ, shows the average trade size increase when there is a future announcement occurring within 30 days of the trade. Interacting the 30d dummy and each of the trading group identifier dummies allow us to study how trade sizes change subject to the release of future corporate announcements. These interaction terms are dubbed $I_{k,i}$, their matching coefficients δ_k measure the isolated effect of the occurrence of a future announcement on the trade size for each categorical group of trader. In order to test hypothesis 4 we added m socioeconomic factors and personal characteristics, $z_{m,i}$ such as income, years of schooling, type of profession, gender, and age to the regression. The coefficients, γ_m, on each socioeconomic factor explain the marginal effect on daily trade value when socioeconomic factors such as income increases by one unit. Further controls are added. Lastly, the regression contains the error term ε_i. We set up the following regression equation using the variables from above:

$$y_i = \beta_0 + \sum_{n=1}^{n=N} \beta_n \, x_{n,i} + \theta 30d + \sum_{k=1}^{k=K} \delta_k \, I_{k,i} + \sum_{m=1}^{m=M} \gamma_m \, z_{m,i} \; + \varepsilon_i$$

As an individual is not guaranteed to trade each year we run a pooled cross-sectional regression instead of using a panel data regression. Pooled cross-sectional regressions are strong when the unit of observations are not necessarily the same each year. Several regressions are conducted, with and without controls and using log trade value as the dependent variable. As mentioned in the data section the log of trade value resembles a normal distribution much more closely than the absolute trade value. Running a log level regression means that for a coefficient of β on the independent variable one would expect the dependent variable to change by $\beta * 100$ %[9]. We use the OLS estimator in order to compute the coefficients in the above pooled cross-sectional regression equation. OLS builds on the notion that errors are normally distributed and that the dependent and independent variables are linearly related to each other. Finally, tests for heteroscedasticity and multicollinearity are conducted to test the robustness of the OLS regression. In order to ensure we get well-behaved test statistics and p-values we use robust standard errors.

Return Study

Furthermore, to examine whether traders profit from their trades, we measure the absolute and abnormal returns for the different traded stocks. We link the specific buys and sells of a stock to the subsequent returns for this trade. This will allow for investigation of whether insiders on average earn more from their trades and how the returns change with the holding period. We use the file used for the

[9] To be exact, the expected change in the dependent variable is $(e^{\beta} - 1) * 100\%$, but for an absolute value less than 0.1 for β these are virtually identical.

pooled cross-sectional regression in this analysis. We investigate returns for all types of traders: insiders, in listed companies, presumed outsiders, family, family insiders, and insider company network traders by taking the average return for each group. Returns for 1 through 30 days are investigated. This allows for the investigation of the final hypothesis:

H4: "*Corporate insiders, their network, and family earn higher returns than the overall population prior to company specific announcements.*"

We investigate both absolute and abnormal in order to understand whether return differences are simply due to access to information or differences in market risk for a holding period of 1 to 30 days. To test whether different trading groups earn different returns, a t-test similar to the one described in the event study methodology is carried out. For the calculation of absolute and abnormal returns please refer to the data section.

The strength of our approach is that it allows for the investigation of hypothesis 4. It is possible to examine whether any difference in the trading activity by different types of insiders also translates into a difference in returns. If this is the case, it lends credibility to the theory that insiders possess non-public information and profit on this through trading. This also warrants future research into the legality of these trades.

This is not a perfect investigation: instead of looking at the actual holding period we investigate the returns following a trade. Furthermore, the paper cannot infer whether transaction costs differ between the types of traders, and whether the corporate insiders can acquire (sell) stocks at favourable prices. The return study is to be understood as a simple proxy for a trading strategy that replicates all trades by a certain type of trader. As most of this data is non-public, this is naturally not a replicable real world trading strategy, but it is indicative of the return development for the different types of traders. To make the results more intuitive and comparable to past scholarship we also calculate the returns on an annual basis. Obviously, these are not the actual annual returns obtained by the traders, but would instead be the returns to our unrealistic proxy trading strategy.

Results

In this section we investigate the research question: "*to which extent can it be argued that corporate insiders and their network are in a privileged position compared to the general public prior to the release of corporate announcements?"*. We divide our answer into three parts. In the first part we examine pre-announcement trading through an event study. The purpose of this approach is to attempt to answer whether insider trading activity rises before announcements, and whether corporate insiders trade in the correct direction before an announcement (hypotheses 1 and 2). In the second part we use a pooled cross-sectional regression study to analyse the trading pattern of insiders while controlling for socioeconomic factors, investigating whether differences in trading behaviour persist when controlling for these (hypothesis 3). In the third part the returns of the different groups of traders are compared to examine whether any difference in trading patterns also translates into a difference in returns (hypothesis 4). Testing hypothesis 4 is important, as exploitation of non-public information should translate into significant returns. Finally we synthesise the results in order to reflect on the overall research question.

Event study

We conduct an event study in order to investigate how insiders trade prior to corporate announcements, testing hypotheses 1 and 2[10]. To test hypothesis 1, the pre-announcement trading pattern of corporate insiders is compared to trades by the trading groups: "in listed company" and "outsiders". In doing so, we generate both an equal-weighted and a value-weighted trading measure. Furthermore we carry out consistency checks to investigate differences in the trading patterns found. Lastly, we investigate hypothesis 2 by restricting the data to only include announcements that resulted in significant price changes. Using this restriction allows us to infer whether corporate insiders correctly predict the price change of the announcement. This test is important, as increased trading activity needs to be accompanied with better predictive abilities for there to be an argument concerning exploitation of non-public information.

[10] H1: *"Insiders' trading activity rises prior to the release of a corporate announcement."* H2: "*Corporate insiders are better at predicting the direction of a significant announcement than outsiders."*

Does Insider Trading Activity Rise Before the Release of corporate announcements?

Equal-Weighted Evidence of Trading Prior to Announcements for All Trade Groups

Figure 4 shows the average deviation in trading volume for the three groups (insiders, "in listed company", and outsiders) from 90 days before the announcement to 21 days after the announcement using equal-weights. Equal weighting implies that the deviation from average trading volume per group is equally weighted for each company. As a result, the largest traded company has the same weight as the smallest traded company when calculating the average. Thus the insider trading volume is not the representative share of insider trading in the market in general. Using this measure insider trading in small companies will be over-weighted while insider trading in large companies will be under-weighted in terms of trading volumes.

From the graph we observe that the relative trading volume for all groups move closely to each other. The three series fluctuate around a deviation level of unity until roughly 10 days prior to the announcement where they collectively follow an increasing trend towards the announcement day. The relative trading measure shows that the trading groups trade significantly more on, and immediately before, announcements. The insider series has a few jumps prior to the announcement that are unmatched by the other two series. This happens around 75-70 days before the announcement. These spikes can suggest two things: 1) that corporate insiders choose to trade 75-70 days prior to announcements or 2) that it is an anomaly caused by a small company with few recorded trading days. We address the latter point later in the results section.

Table 2 provides the average relative trading deviation for the three trading groups for different time intervals. The stars signify whether the means are statistically different from 1, which constitutes a normal trading day. **Table 2** furthermore shows the differences in average relative trading deviation between the three groups, where the stars signify a difference statistically different from zero. Significances are measured using a t-distribution. The table shows, similarly to the graph, that the trading activity for the three different groups is significantly larger than an average day 10 days prior to an announcement. The three means are not statistically different from each other, which implies that there are no systematic differences between the trading patterns of insiders, the individuals in listed companies, and the presumed outsiders shortly before announcements. This finding suggests that the insiders are not at a privileged position compared to the other groups. The increase before an announcement by the non-insiders may be due to information dissemination or extraordinary predictive abilities by the outsiders and "in listed company" group. We investigate information dissemination later in the results section, where the networks of insiders are identified.

Figure 4: Equal-weighted relative trade volume

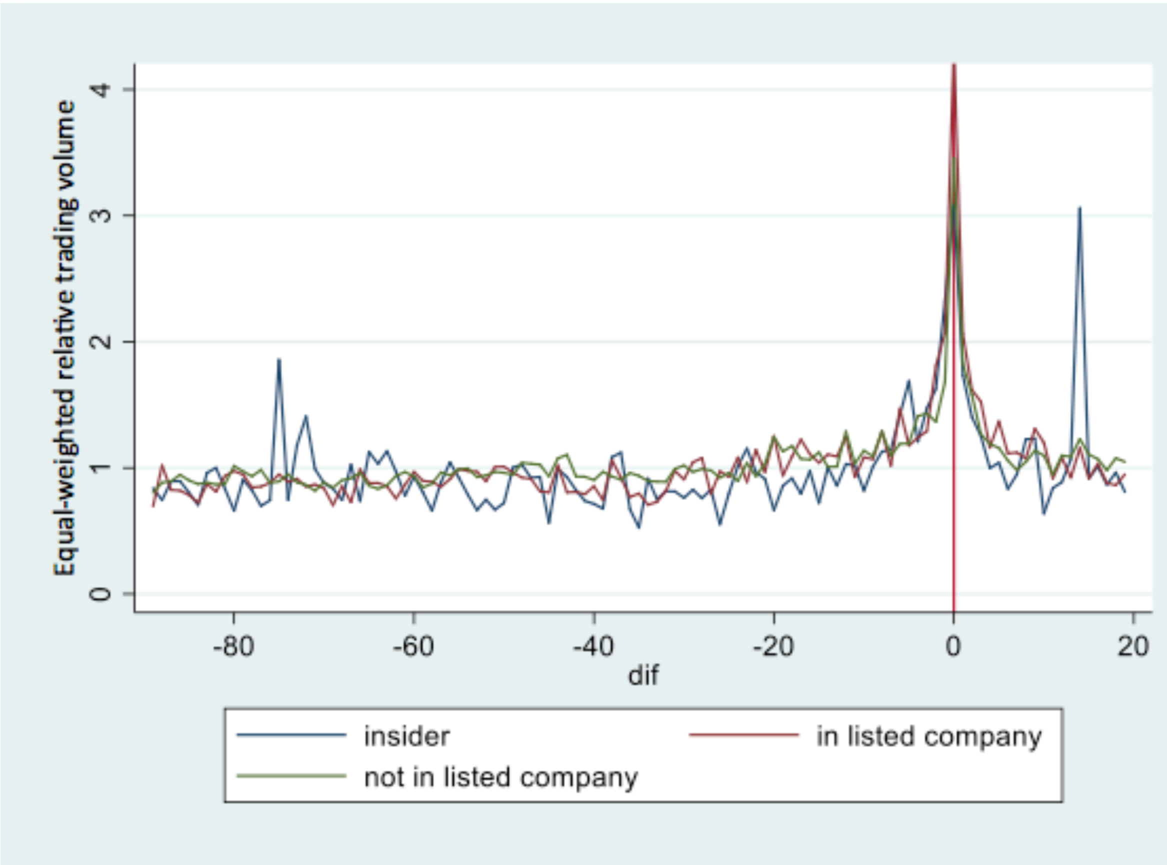


Table 2: significance tests for equal-weighted relative trade volumes

	average deviation			difference between groups		
	insider	in listed	outsider	insider - outsider	insider - in listed	in listed - outsider
-10 days to -1 day	1.38**	1.35**	1.3***	0.1	0.03	0.06
-20 days to -11 days	0.88**	1.1*	1.11**	-0.23***	-0.22***	-0.01
-40 days to -21 days	0.83***	0.91**	0.95***	-0.12**	-0.08	-0.041
-90 days to -41 days	0.89***	0.88***	0.93***	-0.04	0.01	-0.05***
1 day to 20 days	1.14	1.17*	1.15**	-0.04	-0.04	0.00

* p<0.05 ** p<0.01 *** p<0.001

Figure 5: Value-weighted relative trade volume

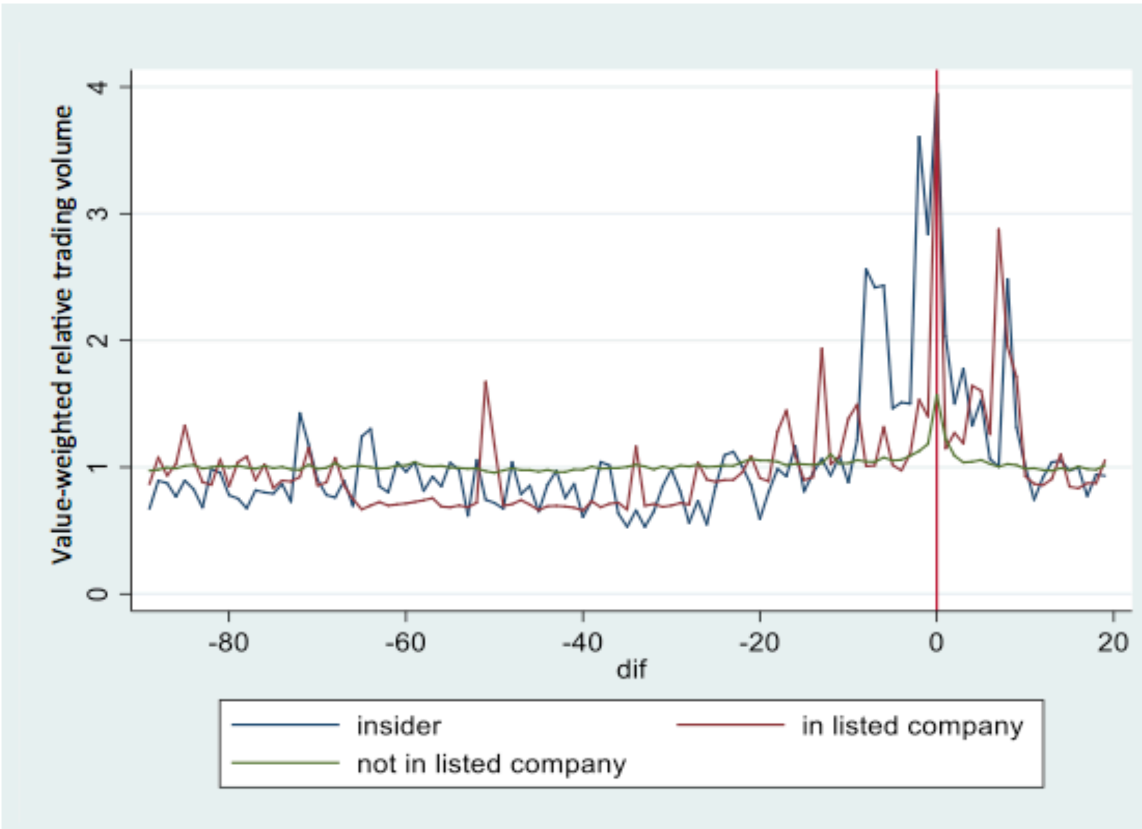


Table 3: significance tests for value-weighted relative trade volumes

	average deviation			difference between groups		
	insider	in listed	outsider	insider - outsider	insider - in listed	in listed - outsider
-10 days to -1 day	2.04**	1.23**	1.08***	0.97**	0.82**	0.15
-20 days to -11 days	0.93	1.15	1.04***	-0.11	-0.22	0.11
-40 days to -21 days	0.79***	0.81***	1.01	-0.22***	-0.02***	-0.2***
-90 days to -41 days	0.85***	0.86***	0.99*	-0.13***	0.01	-0.14***
1 day to 20 days	1.22*	1.25*	1.02	0.21	-0.02	0.23

* p<0.05 ** p<0.01 *** p<0.001

A Value-Weighted Approach: Insiders Trade Relatively More Prior to Announcements

For the previous graph we generated equal weights to assess deviations in trading volume for the different stakeholders on company level. However, as trading volume is a proxy for the amount of money invested in each company, we argue that there is a case for analysing the trading patterns using a value-weighted approach. We are interested in examining how prevalent insider trading is on market level, and thus larger trading volumes should account for more. **Figure 5** shows the value-weighted deviations from the average trading level across the entire sample. It is now evident that there is a significant difference between the trading behaviour of the three groups of traders.

Throughout the entire period, the "outsiders" group floats around unity with a low volatility. On the announcement day we observe that the trading volume increases by slightly less than 50% compared to the other trading days. **Table 3,** similarly to **table 2,** shows the average relative trading deviation for the different groups, and the differences in this variable between the groups. **From table 3** we observe that the outsiders' average deviation level in the 10 days before an announcement is 8% larger than normal trading days, which is statistically significant. This marks a mild increase in trading activity, and suggests knowledge dissemination.

The trading group "in listed company" exhibits a more volatile trading pattern prior to announcements than the "outsider" group. Throughout the 90 days prior to the announcement we observe several large positive trading volume deviations for the individuals in listed companies. Spikes in deviations become more evident the closer one gets to the announcement. Furthermore, both from **figure 5** and **table 3** it is evident that the group trades more 10 days prior to an announcement. This increase is not significantly larger than for the outsiders. This suggests that trading behaviour increases mildly before corporate announcement for the "in listed company" group, however this trading behaviour does not appear very systematic. This may be caused by various reasons: firstly, as this group consists of traders who are professionally linked to *a* listed company[11] the group is large, and it is thus questionable whether the entire group possess insider information. As a result, any trading pattern gets watered down by the uninformed fraction of the traders in the group. Secondly, since certain news are released at the same time every year (financial reports etc.), this may be indicative of speculation concerning the outcome of

[11] Note: the company traded in for that specific observation is *not* the one the trader is directly linked to (through employment), as this constitutes the insider group.

the announcements, and thus not be based on insider information. Lastly, it is worth stressing that the trading volume deviates largely from average trading days on the announcement day. This could potentially indicate that this trading group is better at understanding the content and impact of a corporate announcement than outsiders.

The "insider" group exhibits an interesting and distinguishable trading pattern. From **figure 5** it is evident that the insider trading group exhibits especially large deviations from average trading volumes in the eight days before an announcement is released to the public. **Table 3** reveals that the 10-day average before an announcement is 104% larger than an average trading day. Furthermore, this increase is significantly larger than the outsiders and "in listed company" group, which indicates that the insiders increase their trading volumes by more than any other group. Similarly to the "in listed company" group, the "insider" group exhibits large deviations from average trading volume on the announcement day. We therefore observe that trading activity systematically rises prior to announcement for insider traders. Our findings directly match the research of Ahern (2017), Watson & Young (1999), Meulbroek (1992), and Jeng et al. (2003) that find changes in trading patterns of corporate insiders shortly before corporate announcements. Additionally, this is in line with the prediction of hypothesis 1.

Furthermore, **figure 5** displays an interesting pattern after the announcement day. Until around 14 days after the announcement, we observe that the trading intensity of both the "insider" and the "in listed company" group remains high. Seeing that both groups prior to the announcement increased their trading volume the large post announcement deviation could be explained by the two trading groups reversing their pre-announcement trades in order to profit from the announcement. However, **table 3** shows that the two groups do not trade statistically different from each other or the outsiders. After day 14 the trading volume reverts back to normal for the two groups.

Consistency Check: Share of Total Trading Volume

The insider trading group is a small fraction of the entire population of traders. As a result, the total volume traded is much smaller for the insiders than for the other groups. From **figure 5** we learned that the "insider" group exhibited substantial deviations of trading volume shortly prior to announcements. But is this increase in trading volume also represented in terms of a higher trading share?

Figure 6: Insiders' percentage trade of total trade volume

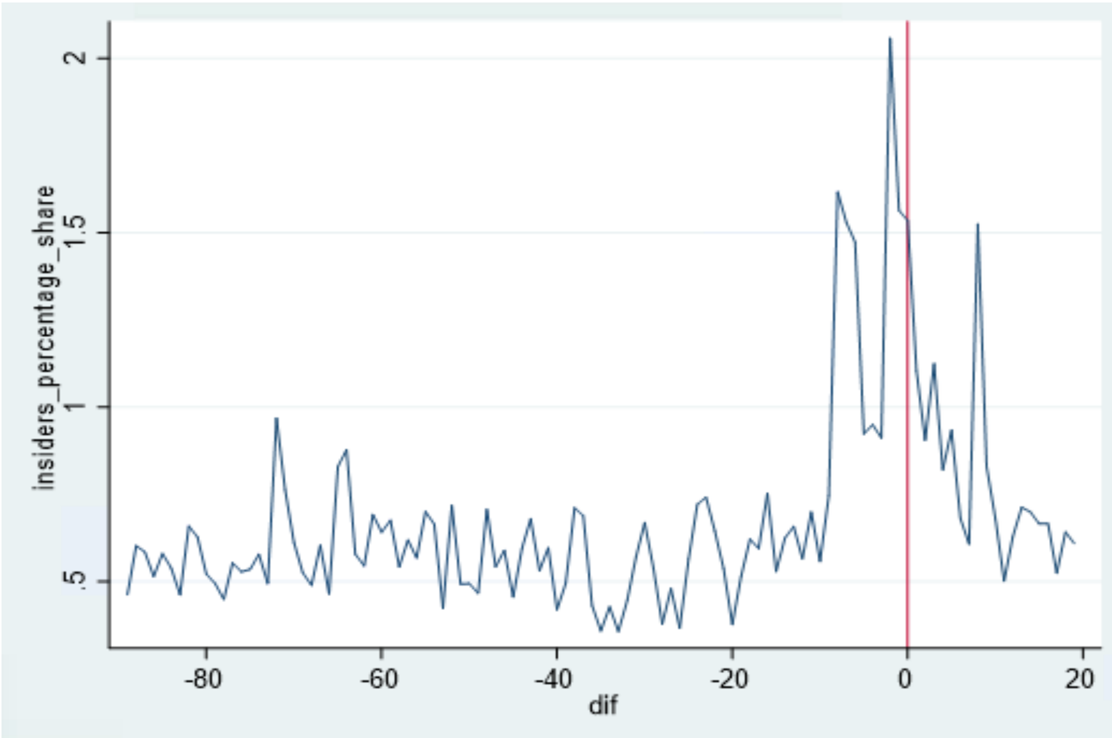


Figure 6 shows the "insider" trading group's share of total daily trading volume around the release of corporate announcements. Similar to the study of Meulbroek (1992) we find that prior to 20 days before an announcement, insider trading constitutes a small fraction of the daily total trading volume. However, from 20 days prior to the announcement and onwards the share of total trading volume conducted by insiders rises substantially from 0.5% to peak at 2% of the total trading volume shortly before the release of the company specific announcement. Thus for the insider group, the share of total daily trading volume increases by 4 times at its peak between t=-20 and t=-1. In conclusion, we learn that the rapid increase in insider trading volume is unmatched by the "outsiders" group. The figure for the outsiders' and the "in listed" group's shares of the total volume traded can be found in **appendix 8**. This indicates that the rapid increase in the trading activity of the insider group is not explained as a general phenomenon for all groups of traders, strengthening the argument that insider traders trade more before company-specific announcements (H1).

Consistency Check: Value vs. Equal weights

The above analysis showed that results differ significantly when using value weights or equal weights to generate the relative trading volume. As equal-weighting assigns the same weight to companies with large trading volumes and companies with small trading volumes, one hypothesis is that insider trading is more prevalent in large companies. To investigate this, we sorted each company in the data set by total trading volume. We then divided companies into three groups of which two are of interest. The first group is classified as "small" companies and comprises all companies with a total trading volume below the 25% percentile. The second group is classified as "big" companies and is constructed by including all companies with a total trading value above the 75% percentile. The third group is the middle group, which consists of all companies with total trading value between the 25% percentile and the 75%.

After splitting the sample into three groups the equal-weighted aggregation method is then repeated, but this time for the "big" and "small" companies. **Appendix 9** repeats the equal-weighted analysis from the small company group. From **appendix 9** it is evident that the trading patterns of the three trading groups are all highly volatile. Due to the high volatility it is impossible to assess whether the three different groups have different trading patterns, and whether the trading patterns change closer to the corporate announcements. These findings can mean two things: 1) that there are few trading days or announcements for small companies, and as a result one large trade is able to skew the deviation level substantially. 2) That corporate insiders shy away from conducting insider trading in small companies, as even a small trade is easily detectable. In the current state of our thesis we are not able to state which explanation drives the results.

Furthermore, we generated the share of trading volume for corporate insiders for small companies, as depicted in **appendix 10**. From **appendix 10** we observe that the insiders' average share of trading volume is much larger than when looking at all companies: we observe that the share on insider trading days leaps up to a maximum of 3%. The evidence is not conclusive, but it could indicate that by even trading small amounts one risks obtaining a large share of the total daily trading volume for small companies. If this is the case it could indicate that the lack of difference between the three trading groups stems from the fact that corporate insiders shy away from trading on inside information in companies with small trading volumes, as it is too difficult to blend into the crowd – even for the smallest trade.

In contrast, when repeating the equal-weighted relative trading analysis for the "big" trading volume companies, as seen in **appendix 11**, we observe a pattern that closer resembles the value-weighted findings, as the three different trading groups now display different trading patterns. The insider trading group once again trades relatively more than the other groups just before announcements. It must, however, be noticed, that both the outsider group and the "not in listed company" group both have one single observation manifested in a large spike prior to the announcement. Furthermore, the insiders' share of the total market volume, displayed in **appendix 12**, resembles the pattern in **figure 6** in magnitude. Thus restricting the equal-weighting to only include large companies resembles the value-weighted findings more.

We have tested what could potentially explain the difference in results from a value and equal based weighting. The findings indicate that the equal-weighted approach suffers relatively more from noise stemming from small companies compared to the value-weighted approach, suggesting that insider trading patterns are more prevalent for companies with large trading volumes.

Do Corporate Insiders Trade in the Right Direction?

We also conducted a consistency check testing whether one can observe intensive trading volumes by corporate insiders prior to announcements where the stock price at least decreased or increased by 5% on the announcement day. **Appendix 13** shows the value-weighted daily trading deviation from average trading days. We find that insider trading occurs prior to significant announcements, further suggesting that some insiders may be exploiting non-public information. It is now relevant to investigate the direction of the trades, testing hypothesis 2.

In order to test whether corporate insiders trade in the right direction we calculated the share of buys over total transactions (the purchase ratio). For insiders throughout the entire period, including both increases and decreases, the share of stock purchases equals 51.12% which is not statistically different from 50%, as shown in **table 4**. Stars signify statistical significance at the 5% level using the t-distribution.

Table 4: purchase ratios for the different groups

		insiders	in listed	outsiders
	entire sample	51.12%	53.42%*	55.08%*
price increase	**-30 days < trade < announcement**	**67.46%***	**54.96%***	**56.48%***
	-80 days < trade < -30 days	48.57%	52.09%*	54.15%*
price decrease	**-30 days < trade < announcement**	**30.91%***	**51.01%**	**52.67%***
	-80 days < trade < -30 days	52.54%	50.27%	52.70%

The table shows the purchase ratio for each trading group for different time periods. Stars signify that the ratio is statistically different from 50% with 5% statistical significance.

However, as shown in **table 4**, when the stock price increases by more than 5% we find that the purchase ratio for insiders equals 67.46%, which is statistically different from 50%, and is statistically different and larger in magnitude than the two other trading groups. This indicates that most of the corporate insiders, that execute trades within 30 days prior a significant announcement, correctly predict the direction of a positive announcement. A similar pattern is revealed when studying the trading behaviour of the corporate insiders 30 days prior to a significant decrease in the stock price. The share of purchases equals 30.91%, which is statistically different from 50% and is lower in magnitude and statistically different from the two other trading groups. Once again, there is a significant and substantially larger fraction of corporate insiders that are able to predict the outcome of an announcement that changes price. The period between 80 days to 30 days before announcement is however not different from 50% neither for increases nor decreases. This indicates that corporate insiders trade and thereby signal the direction of the announcement only in the very short run.

In comparison, as shown in **table 4**, the outsider group had an average purchase ratio of 55.08% for the entire sample, 56.48% purchase share for positive announcements, and a 52.67 % purchase share for negative announcements - all point estimates were statistically different from 50%. A similar result emerged for the "in listed company" trading group, which had an average purchasing ratio of 53.42% for all days, a 54.96% share for positive announcements, and a purchase share of 51.01% for negative announcements. With the exclusion of the latter, these shares were significantly different from 50%. From the trading behaviour of the groups "outsiders" and "in listed companies" we observe that on average the two trading groups purchase more stocks than they sell in both up and down scenarios. Thus the purchase ratios for the "outsiders" and "in listed company" do not seem to strongly predict the direction of future announcements. The mild increases in trading volume for the "in listed company" group and the outsiders do not seem to be caused by more informed trading, as the purchase ratios for positive and negative announcements are only marginally different but might still suggest slight knowledge dissemination. Therefore it is relevant to attempt to extend our definition of insiders by mapping the network of corporate insiders. This is done in the two following sections.

The above findings indicate that the insider group is at a privileged position compared to the two other groups. The fact that the purchase ratios of the insider and "in listed company" groups are significantly different, implies that the predictive power of the insiders does not stem from knowledge of being in *a* firm but being in *the* firm. Furthermore, since neither of the purchase ratios of the outsiders nor the "in listed companies" groups are strong predictors of the direction of the announcement, we argue that one does not become better at correctly predicting the outcome of company-specific announcements by being associated with another listed company.

Compared to existing academic scholarship our finding is unique. Academic scholarship has only mildly succeeded in predicting positive announcements when looking at cross sectional evidence of insider trading (Elliott, Morse, & Richardson, 1984), (Lakonishok & Lee, 2001). Furthermore, the buy ratio matches the findings of Lorie & Niederhoffer (1968) for positive announcements. Only Cohen et al., (2012) are able to find evidence of prediction of both positive and negative announcements from trading patterns of board members. We conclude that corporate insiders on average succeed in predicting the direction of a significant announcement, which neither traders from the "outsiders" nor "in listed company" groups are able to. This finding is exactly what was stated in hypothesis 3: insiders trade in the right direction.

Lastly, we earlier found a surge in trading activity after the release of a corporate announcement. Post-announcement trading could be due to individuals reversing their pre-announcement trades to reap the benefit of the price change. For the insider category, we find that 21 days after a negative announcement the purchase ratio for insiders is equal to 63.16%, which is statistically different from 50%, as shown in **appendix 14**. This could imply that corporate insiders rebuy the stock after selling it prior to the announcement. However, this result is only indicative, as we do not test whether it is the same individual that trend reverses. Furthermore, we find a statistically insignificant 45.34% purchase ratio following positive announcements. The results show a striking trend of trade reversal in the period following negative announcements, but not for positive announcements. Whether it is the same person that reverses her trade is, however, beyond the scope of our master's thesis.

Event Study Conclusion: Insiders Trade More and in the Correct Direction

We studied the trading behaviour of three trading groups: outsiders, "in listed company" and insiders. We found that trading volume increases sharply shortly prior to announcements for corporate insiders. This result is most evident for large companies. We find that the share of the total traded daily volume increases for the insider group immediately before announcements. This implies that increases in insider trading activity are not a function of an overall increase of trading activity by all agents in the market. These findings suggest that hypothesis 1 holds; that corporate insider trading activity rises prior to corporate announcements. Furthermore, both the "in listed company" group and the presumed outsiders exhibited an increase in trading volume just before announcements. To investigate this potential knowledge dissemination we extend the analysis to include the network of corporate insiders.

To test hypothesis 2, we identified all announcements in the sample that had a daily absolute return larger than 5%. These significant announcements were then used to investigate the direction of trading prior to announcements for the different types of traders. We found evidence that the corporate insider group is able to predict the pricing outcome of a future announcement in the short run. In comparison, neither the outsiders nor "the in listed company" group exhibit similar predictive abilities. This fuels the argument that subsets of corporate insiders exploit insider information in the market, supporting hypothesis 2. However, whether corporate insiders make money on pre-announcement trades, and whether personal characteristics can explain differences in trading patterns is addressed in the following sections.

Do Differences in Trading Patterns Persist When Controlling for Socioeconomic Factors?

The potential issue with the event study is that the aggregation method disregards individual characteristics, which could result in omitted variable bias. In the data section we showed that the three types of traders have different personal characteristics. This poses a potential problem for our findings in the event study, as it is not possible to show whether the difference in trading activity is due to personal characteristics or from being an insider. A pooled cross-sectional regression study overcomes this issue as we test hypothesis 3[12] by controlling for socioeconomic factors such as education, job type, and income. Since we through the event study found increased trading activity for both insiders, the "in listed company" groups, and outsiders before an announcement, we investigate the trading behaviour of other groups that potentially can be linked to the insiders. These groups are family members and the professional network.

As mentioned previously, the log of the individual trade value is used as the dependent variable. **Table 5** provides regression results using this dependent variable. Column 1 is a simple regression only looking at the trade group dummies and column 2 includes interaction dummies to measure the effect of being an insider *and* the occurrence of an announcement in the 30 days following the trade. Column 3 adds personal and socioeconomic characteristics together with additional time controls to the regression in column 2. **Appendix 15** shows the full regression results using both the absolute and log trade value. **Appendix 16** and **17** provide tests for multicollinearity and heteroscedasticity respectively. As shown, the variance inflation factor (VIF) for all variables is less than 10, and thus we do not expect multicollinearity to be an issue for any of the regressions. Heteroscedasticity is clearly evident in all of the OLS regressions, which is why we report the regression results in **table 5** and **appendix 15** with robust standard errors.

A few coefficients and variables are specifically worth noting: first of all, the coefficient on being an insider is *negative* and significant when controlling for socioeconomic factors. Thus, from column 3 we find that insiders' trade values are 49% smaller than the average trade value[13]. However, the interaction term between being an insider and the occurrence of an announcement within thirty days after a trade is large, positive and statistically significant.This means that, all else equal, if an individual is an insider she trades for *225% more* thirty days before an announcement. This finding is similar to what was found in the event study, namely that insiders increase their trading volume by more than other groups prior to announcements. We thus find that controlling for socioeconomic factors does not change the conclusion from the event study, in line with the prediction of hypothesis 3.

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[12] H3: "*Differences in trading patterns are not explained by socioeconomic factors.*"

[13] This result is obtained by using the transformation method mentioned previously: change in the dependent variable = $(e^{\beta} - 1) * 100\%$.

Table 5: regression output for log trade value

	(1) simple	(2) interaction terms	(3) with characteristics
insider	1.616***	-0.286	-0.686**
	(17.3)	(1.22)	(2.75)
family insider	-0.0692	0.158	0.393**
	(0.99)	(1.04)	(2.67)
company network insider	0.441***	0.352*	0.401**
	(7.32)	(2.38)	(2.66)
dummy for an announcement in the 30 days following a trade	0.309***	0.310***	0.322***
	(220.98)	(219.38)	(228.72)
insider *and* an announcement 30 days after the trade		1.292***	1.178***
		(6.12)	(5.61)
family insider *and* an announcement 30 days after the trade		-0.185	-0.309*
		(1.30)	(2.22)
company network insider *and* an announcement 30 days after the trade		0.126	-0.189
		(0.96)	(1.35)
trade on day of announcement			-0.0657***
			(119.35)
simple dummies	yes	yes	yes
with interaction terms	no	yes	yes
with personal characteristics and other controls	no	no	yes
N	8222972	8222972	7494242

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

The full set of dummies, interaction terms, personal characteristics, and other controls can be found in appendix 15

Information Dissemination?

The coefficient for the dummy regarding the occurrence of an announcement thirty days after the trade is statistically significant and positive. This finding implies that trades on average are 38% larger before announcements for the outsiders. This could indicate the existence of information dissemination prior to announcements, that there are some insiders we have not correctly identified, or that traders are able to anticipate announcements. We are not able to determine which explanation is most likely, however, in the return study we show that the outsiders are not able to generate any significant abnormal returns. This observation matches our findings from the event study: trading volume increased mildly for non-insiders immediately before announcements.

Furthermore, it is worth noting that the coefficient on the announcement day is negative and statistically significant. Since it was shown in the event study that the total trading volume increased for the announcement day, this implies that on the announcement day significantly more trades are carried out, with the average trade size being smaller than the average trade size on a day without an announcement.

Trading Activity by the Family and Professional Network

Ahern (2017) finds that insiders often pass on non-public information to their relatives and professional network. Interestingly, for the two network-based insiders, family insiders and network traders, the coefficients are positive and statistically significant. Thus, family insiders trade for 48% more than the population on average. When interacting with the dummy for the occurrence of an announcement, the coefficient is negative and significant. Combined with the 30d dummy this implies that the family insiders do not change their trade size around announcements. This is a somewhat surprising finding, since the insiders trade for more around announcements. The finding does not seem to suggest that families exploit insider information, however, this will be examined in further detail in the returns section, as smaller trade values do not necessarily imply no insider trading.

The professional network insiders also trade for more than the population on average; this figure is 49%. The coefficient of the interaction with the dummy for the occurrence of an announcement is not statistically significant.

Regression Conclusion: Corporate Insiders Trade Larger Amounts Prior to Announcements

Our pooled cross-sectional regression study supports our event study finding, that insiders trade significantly more before an announcement. This is important, since it proves that the difference in trading pattern persists even when controlling for individual characteristics, as predicted by hypothesis 3. Combined with the finding that insiders trade in the correct direction before a significant announcement, we expect to observe that insiders earn statistically significant positive returns from their trades. In the following section, exactly this will be investigated: do insiders profit from their trades, and if so, do they profit significantly more than the presumed outsiders? The pattern mentioned above was not found in the network of the corporate insiders, however, smaller trade values do not necessarily imply no insider trading. Therefore, returns for the family and company network insiders will also be investigated as a further check.

Does Increased Trading Activity Translate Into Financial Gains?

We examine whether the difference in trading patterns, found previously in the results section, also translates into differences in returns, investigating hypothesis 4[14]. It is important to investigate this hypothesis, as the realised return should be the crux of illegal insider trading. Both absolute and abnormal returns will be investigated. This ensures that it is possible to investigate whether any large absolute returns are due to a larger market risk.

First and foremost, **appendix 18** is a simple visualisation of the average absolute returns for the entire population for a holding period of 1 through 30 days after a trade. The graph shows that returns, on average, revolve just around zero in the days immediately following a trade. This is (almost) in accordance with efficient market hypothesis that states that stock price movements are a random walk, implying that returns from trades should be zero in the short run. The reason that this is not perfectly in accordance with efficient market theory is that many of these returns indeed are significantly different from zero, although not at a level that is equivalent to more than a 1% annual return, and thus could be argued to not be of economic significance. **Appendix 19** shows that the average abnormal return for all trades is less than zero. The average 30-day abnormal return corresponds to an annual abnormal return of roughly -1%. This indicates that the average trader did not perform better than the market, which is

[14] H4: "*Corporate insiders, their network, and family earn higher returns than the overall population prior to company specific announcements.*"

consistent with the efficient market hypothesis. These findings support the validity of our return estimates. **Appendix 20** provides the same results for the consistency check where the risk-free rate is set to be 1% annually, and is almost identical to the results obtained using a risk-free rate of 0%.

Table 6: absolute and abnormal returns for insider traders

	absolute returns for insiders				abnormal returns for insiders			
	no restriction		30d = 1		no restriction		30d = 1	
days	mean	annualised	mean	annualised	mean	annualised	mean	annualised
1	0.00193391*	62%*	0.0025541*	89%*	0.00168725	52%	0.00274767*	99%*
7	0.00475572*	18%*	0.0058407*	23%*	0.00300292	11%	0.00440428*	17%*
30	0.0054045	7%	0.00293951	4%	0.00327817	4%	0.00269742	3%

The table shows insiders' returns for different holding periods. Stars signify that the value is statistically different from 0 with 5% statistical significance.

Table 6 summarises insiders' returns, annualised returns, and whether they are statistically significant at the 95% level. **Appendix 21** reports these findings in full together with the t-statistics. What is worth noting is that they are positive and statistically significant in the days immediately following a trade, but become statistically indifferent from zero when the horizon is longer than 7 days. This is an interesting finding, as it implies that the insiders trade with a short horizon in mind or trade right before price changes. Furthermore, it is in line with what was found in figure 5 in the event study, where insiders' trading activity rises sharply and significantly 8 days before an announcement. When comparing trades with at least one announcement occurring within 30 days of the trade to trades without such restrictions, the short-term returns for insiders are different. This implies that the insiders make their returns around announcements and not because they just have a better understanding of the market and their firm in general. These results and conclusions hold when looking at abnormal returns. Conditioning on the trade being within thirty days before an announcement, the seven-day abnormal returns translate into *abnormal* returns of 17% over a year. The one-day abnormal returns translate into an annual abnormal return of 99%, which is far larger than historic returns generated by hedge fund managers and famous investors (Frazzini, Kabiller, & Pedersen, 2013).

The returns for family insiders are interesting because they display a pattern that is much different to that of the insiders, as shown in **table 7**, where the stars signify statistical significance from the t-distribution. The full list of returns can be found in **appendix 22**. In the short horizon the returns resembles that of the average trader much more than the insiders, and are not statistically different from zero. When looking at 30-day returns, in contrast, the family insiders perform much better than both the insiders and the population at large. This holds both when looking at absolute and abnormal returns. As with the insiders, this finding is even stronger when conditioning on the occurrence of an announcement in the 30 days following a trade; the 30-day abnormal return earned by family insiders is equivalent to a 33% annual abnormal return.

Table 7: absolute and abnormal returns for family insiders

	absolute returns for insider family				**abnormal returns for insider family**			
	no restriction		30d = 1		no restriction		30d = 1	
days	mean	annualised	mean	annualised	mean	Annualized	mean	annualised
1	0.00183271	58%	0.00145834	44%	0.00221332	74%	0.00110803	32%
7	-0.00011274	0%	0.00020392	1%	-0.00164366	-6%	-0.00239045	-8%
30	0.01816789*	24%*	0.02958271*	42%*	0.0163125*	21%*	0.02382974*	33%*

The table shows family insiders' returns for different holding periods. Stars signify that the value is statistically different from 0 with 5% statistical significance.

Appendix 23 shows that these findings are not replicated when looking at the non-insider relatives[15]. The absolute returns are significant, though not equivalent to more than 3% on an annual basis. When investigating the abnormal returns, the returns disappear altogether. We interpret this as an indication of the traders having superior knowledge of their own company but not of other companies or the market in general.

The returns for the company network insiders are not statistically significant, which could imply that the professional network has not been properly specified, or that they do not receive insider information. **Appendix 24** reports these findings.

Insiders Earn More Than Others When Trading Before Announcements

Table 8 shows the key returns conditional on the trade taking place within 30 days prior to an announcement for the insiders, individuals in listed companies, and presumed outsiders. Columns 4, 5 and 6 show the differences in returns for the three different groups. **Table 9** has the same structure but instead conditions on there being no announcement in the 30 days following a trade. **Appendix 25** and **26** report the full results. First and foremost, in the longer horizon no differences are statistically

[15] Thus, these are traders who are linked to a listed company via family, but trade in *another* listed company.

significant. This does not come as a surprise, as returns for both insiders and "in listed company" were previously shown to be statistically insignificant in the longer term. What is especially worth noting is that the differences between groups are most pronounced conditional on there being an announcement within thirty days of the trade. For the first seven days after a trade, returns for individuals in listed companies are significantly larger than the presumed outsiders. Furthermore, the returns for the insiders are significantly larger than for individuals "in listed company". Since announcements have not been selected on a significant price change, this indicates that both insiders and individuals in listed companies are significantly better at trading before the right announcements and in the correct direction. Furthermore, it appears that individuals are even better at trading before the right announcements when trading in their own company. These findings are replicated when investigating abnormal returns: before announcements insiders earn significantly larger *abnormal* returns than the two other types of traders, as shown in **table 10** and **appendix 27**. What is especially interesting is that abnormal returns are not statistically different between the three types in the absence of announcements. This can be seen from **appendix 28**. This amplifies the conclusion that the average insider (and individuals in listed companies) earns his return from trading on and around announcements. Furthermore, it indicates that the returns earned by the insiders relative to the average trader are not compensation for extra market risk. Instead, it seems plausible that the returns stem from the exploitation of non-public information by some insiders

Conclusion: Insiders and Their Families Profit Significantly

In our return investigation we find that insiders and family insiders indeed do earn higher returns from their trades than the presumed outsiders, and that these returns are significantly larger when there is an announcement within the thirty days after the trade. This implies that insiders are better at trading before the right announcements than the average trader, which holds for both "true" insiders and the family insiders. This is in partial support of the fourth and final hypothesis: both insiders and their families earn higher returns than the overall population prior to company specific announcements. However, the returns are only present when the family trades in the company they are related to. No such returns were found for the professional network. Once again, the results suggest the exploitation of non-public information.

Table 8: differences in absolute returns for 30d = 1

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider mean /sd	in listed mean /sd	insider mean /sd	(2) – (1) dif/t	(3) – (1) dif/t	(3) – (2) dif/t
1-day return	-0.0002	0.0001	0.0026	0.0003*	0.0027*	0.0025*
	(0.03)	(0.03)	(0.03)	[2.16]	[2.41]	[2.32]
2-day return	-0.0002	0.0004	0.0034	0.0005**	0.0036*	0.0031*
	(0.04)	(0.04)	(0.03)	[2.95]	[2.32]	[2.15]
3-day return	-0.0004	0.0002	0.0041	0.0006**	0.0045*	0.0039*
	(0.05)	(0.04)	(0.04)	[2.91]	[2.50]	[2.43]
4-day return	-0.0005	0.0002	0.0049	0.0007**	0.0054**	0.0047*
	(0.05)	(0.05)	(0.04)	[2.88]	[2.65]	[2.57]
5-day return	-0.0005	0.0002	0.0044	0.0006*	0.0049*	0.0042*
	(0.06)	(0.05)	(0.04)	[2.49]	[2.15]	[2.13]
6-day return	-0.0003	0.0002	0.0049	0.0005	0.0052*	0.0047*
	(0.07)	(0.06)	(0.05)	[1.86]	[2.11]	[2.18]
7-day return	-0.0003	0.0005	0.0058	0.0007*	0.0061*	0.0054*
	(0.07)	(0.06)	(0.05)	[2.38]	[2.32]	[2.33]
8-day return	-0.0001	0.0006	0.0043	0.0008*	0.0044	0.0036
	(0.07)	(0.07)	(0.06)	[2.47]	[1.60]	[1.48]
9-day return	-0.0001	0.0009	0.0044	0.0010**	0.0044	0.0035
	(0.08)	(0.07)	(0.06)	[2.96]	[1.53]	[1.32]
10-day return	0	0.0011	0.0045	0.0010**	0.0045	0.0034
	(0.08)	(0.07)	(0.06)	[3.02]	[1.46]	[1.23]

* p<0.05 ** p<0.01 *** p<0.001

Table 9: differences in absolute returns for 30d = 0

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider Mean /sd	in listed mean /sd	insider mean /sd	dif 1,2 dif/t	dif 1,3 dif/t	dif 2, 3 dif/t
1-day return	-0.0001	0.0004	-0.0001	0.0005*	0.0001	-0.0004
	0.03	0.03	0.02	[2.03]	[0.02]	[-0.22]
2-day return	0	0.0007	-0.0011	0.0007*	-0.0012	-0.0019
	0.05	0.04	0.03	[2.22]	[-0.37]	[-0.69]
3-day return	0.0001	0.0012	-0.0002	0.0011**	-0.0003	-0.0014
	0.05	0.06	0.04	[2.78]	[-0.09]	[-0.37]
4-day return	0.0001	0.001	-0.0007	0.0008*	-0.0008	-0.0017
	0.06	0.06	0.04	[1.98]	[-0.21]	[-0.40]
5-day return	0	0.0009	0.0023	0.0008	0.0023	0.0014
	0.06	0.06	0.04	[1.83]	[0.52]	[0.36]
6-day return	-0.0002	0.0005	0.0036	0.0007	0.0038	0.0031
	0.07	0.07	0.04	[1.47]	[0.81]	[0.66]
7-day return	-0.0003	0.0003	0.0012	0.0006	0.0015	0.0009
	0.07	0.07	0.04	[1.11]	[0.29]	[0.18]
8-day return	-0.0002	0.0004	0.004	0.0006	0.0042	0.0036
	0.08	0.08	0.04	[1.06]	[0.81]	[0.68]
9-day return	-0.0002	0.0005	0.0036	0.0007	0.0038	0.0031
	0.08	0.08	0.05	[1.13]	[0.69]	[0.58]
10-day return	-0.0002	0.0006	0.0022	0.0007	0.0024	0.0016
	0.08	0.08	0.05	[1.19]	[0.42]	[0.30]

* p<0.05 ** p<0.01 *** p<0.001

Table 10: differences in abnormal returns for 30d = 1

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider	in listed	insider	dif 1,2	dif 1,3	dif 2,3
	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t
1-day return	-0.0001	0.0001	0.0027	0.0002	0.0028**	0.0026**
	0.03	0.02	0.03	[1.73]	[2.72]	[2.74]
2-day return	-0.0002	0.0001	0.0031	0.0003*	0.0033*	0.0030*
	0.04	0.03	0.03	[2.11]	[2.37]	[2.34]
3-day return	-0.0004	-0.0001	0.0028	0.0004*	0.0033*	0.0029*
	0.04	0.04	0.04	[2.05]	[2.04]	[2.08]
4-day return	-0.0006	-0.0003	0.0031	0.0003	0.0037*	0.0034*
	0.05	0.04	0.04	[1.65]	[2.02]	[2.08]
5-day return	-0.0008	-0.0005	0.0029	0.0003	0.0037	0.0034
	0.05	0.05	0.04	[1.36]	[1.82]	[1.95]
6-day return	-0.0007	-0.0005	0.0035	0.0003	0.0042	0.0040*
	0.06	0.05	0.05	[1.11]	[1.92]	[2.11]
7-day return	-0.0008	-0.0004	0.0044	0.0004	0.0052*	0.0048*
	0.06	0.05	0.05	[1.36]	[2.20]	[2.38]
8-day return	-0.0007	-0.0003	0.0029	0.0004	0.0036	0.0032
	0.06	0.06	0.05	[1.59]	[1.48]	[1.49]
9-day return	-0.0008	-0.0002	0.0028	0.0006*	0.0037	0.0031
	0.07	0.06	0.05	[2.05]	[1.42]	[1.34]
10-day return	-0.0008	-0.0002	0.0035	0.0006*	0.0043	0.0037
	0.07	0.06	0.05	[2.00]	[1.61]	[1.55]

* p<0.05 ** p<0.01 *** p<0.001

Synthesis of the Results

In the results section we investigated whether corporate insiders and their network are in a privileged position compared to the general public prior to the release of corporate announcements.

From the event study we found that insiders' trading activity rises prior to announcements, and that this increase is significantly different to that of both outsiders and the "in listed company" group on market level. This is in favour of hypothesis 1. Furthermore, when restricting announcements to only include the ones resulting in significant price changes, corporate insiders were found to trade in favour of the announcements. This pattern was not found for any of the other groups. Thus, hypothesis 2 also seems to hold. We showed through a pooled cross-sectional regression study that the difference in trading pattern persists when controlling for socioeconomic factors. This indicates that it is information, and not characteristics, that causes the differences in trading patterns, in line with hypothesis 3. Finally, we showed that insider trades generate high returns in the very short run, while their family profited in the longer term. No abnormal returns were found for the professional network. These findings are partially in line with hypothesis 4.

Our findings suggest that there is evidence of insiders exploiting non-public information. Corporate insiders trade more before announcements, they trade in the correct direction, and they and their families profit from these trades. These results indicate that corporate insiders and their families are in a privileged position vis-á-vis other investors.

Potential Caveats and Further Work

We discuss potential caveats related to our choice of method and on the findings made in our study. Furthermore, we reflect on potential future research, inspired by these caveats.

Do Insider Traders Reverse Their Trades After an Announcement?

In the event study results section we found that a substantial fraction of insider trades prior to a significant corporate announcement is in the same trading direction as the pricing impact of the corporate announcement. Furthermore, we found that this trading pattern reverses after the announcement. This could be indicative of insider traders reversing their pre-announcement trades in order to profit from the initial trade. However, since our finding was only studied on the aggregate level and not on individual level, we cannot conclude that the pre-announcement and the post-announcement patterns are by the same individuals. Another explanation could be that corporate insiders, who did not participate in the pre-announcement trading, have a better understanding of the true pricing impact of announcement and as a result trade if the market overreacted or underreacted to the release of the announcement. As a result, it is interesting to test whether pre- and post-announcement trades are carried out by the same corporate insider, or how long it takes before a pre-announcement trader reverses her trade. Further work should therefore investigate this matter in depth, as finding evidence trade of reversal could help regulators construct a strong case in proving insider trading behaviour in court.

Do Noise Traders Bias the Picture?

Cohen et al. (2012) showed that approximately half of reported trades by corporate insiders are noise, as insiders trade for other reasons than profit such as diversification and liquidity. These noise (routine) traders were not found to be informative, and investing in their trades generated insignificant returns. A natural extension of our master's thesis would therefore be to apply the filter of Cohen et al. (2012) in order to remove noise traders. We decided not to perform this filtering due to two reasons.

Firstly, using the Cohen filter poses tough requirements on the sample size, as the authors used three years of past trading history to divide traders into "routine" and "opportunistic" trading groups. This is a substantial challenge since our dataset contains observations from January 2012 to December 2016. Using the Cohen filtering process would limit the sample to two years of observation, reducing the sample size with 60%, which we found too significant.

Secondly, the overall purpose of our study differs from the paper of Cohen. The purpose of Cohen's paper is to build trading strategies on publicly assessable data while our master's thesis uses non-public data in order to investigate whether insiders and their network are in a privileged position in the Danish economy. Our study does not aim at generating realistic trading strategies that can be replicated by finance professionals.

Using the filtering process would be a sound addition to our study. Therefore, further work should in a few years, from the time of writing, apply the filtering process. However, in contrast to Cohen et al. (2012) we find evidence of predictable insider trading patterns both from the event study, but also from studying the returns of insiders. Since routine traders are expected to trade evenly among the year, the results found by our master's thesis are thus even stronger considering that we are able to distinguish positive and negative announcements from each other. As a result, removing routine traders would only improve the magnitude of a ratio that already shows that corporate insiders are better at predicting the direction of an announcement compared to all other trading groups.

Trading in the Network

We found that the insider trades of families of corporate insiders generate substantial returns, while the return for the professional network was insignificant. This partially confirms the finding of Ahern (2017) who discovered that insider information sprawls out from the original tipper like the branches of a tree. Insider information was found by Ahern to be shared through family ties, through the professional network, and through social relationship such as geographic proximity and having gone to the same school. Furthermore, Ahern finds that the trading effect is largest in the third link of the network. As we only study the first link of family ties and of the professional network of an insider much can be done. For both the professional network and social ties the task is rather difficult. To overcome the problem of social ties one could potentially exploit the use of big data from social media. Social media data could be a strong tool as one could easier map several links of social interaction by using proxies such as friends on Facebook compared to using measures of social interaction such as geographic proximity. For professional networks one could either use data from LinkedIn or continue the network analysis for the professional network used in our master's thesis. Adding more network links to both social ties, family ties, and the professional network would further the understanding of how far on average information travels in the networks of corporate insiders.

A Note on Returns

We found that, in contrast to the overall trading population, corporate insiders and relatives of corporate insiders earn high absolute and CAPM adjusted abnormal returns from trading before announcements. Another return method could be to use more factors in calculating risk-adjusted returns. The literature has previously used the Fama-French factors (market, SMB, and HML) and momentum to obtain risk adjusted returns (Jeng et al., 2003).

The choice between CAPM abnormal returns and abnormal returns from factor models depends on the access to index funds. As momentum, SMB and HML are expensive to buy, Pedersen (2015) suggests that CAPM should be used if one does not consider returns from the perspective of institutional investors or hedge funds. As we study the returns of individuals, abnormal returns on CAPM seems the most suitable proxy. However, since the insiders are wealthy individuals, as shown in the data section, they may have a cost of trading more similar to institutional investors. It may therefore be worthwhile to investigate the abnormal returns using factor models.

Do Insider Trades Move the Market?

We found that the pre-announcement returns on trades by corporate insiders amounted to an annualised return of 99% for a holding period of one day and 17 % annualised abnormal return for a 7 day holding period. This finding suggests that corporate insiders trade right before price changes. However, this finding is potentially exposed to reverse causality, as reported insider transactions are often replicated by sophisticated investors such as hedge funds. The price change might be a product of increased trading activity by trade mimickers instead of due to corporate announcements. Future research should therefore try to breach this caveat by investigating the price impact of insider trading days by using different versions of a modified market model as used in Ahern (2017), Chakravarty & Mcconnell (1999), Cornell & Sirri (1992), and Meulbroek (1992). However, from **appendix 24** we observe that insider trades without the release of a future announcement within 30 days yields a non-significant daily return of -0.0001 which annualized give a return of -2.5 %. Unless professional investors are able to single out all opportunistic and non-opportunistic trades there appears to be no initial evidence for reverse causality.

Inclusion of Further Insider Transactions and Court Data

Our dataset contains individual transaction made by all registered personal trading accounts of all Danes. As a result, neither transactions from foreign trading accounts nor transactions carried out through companies are included. Using foreign accounts or trading through a private company can be used as a way to hide an insider trade. No scholarship has specifically studied the prevalence of using foreign accounts or private companies for insider trading. Several court cases both in Denmark and the US show that insiders use other accounts than their own to conduct insider trading (Bentow, 2010; McCoy, 2017). It is therefore necessary for future research to link foreign transactions and transactions carried out through private companies to corporate insiders. Using our dataset linking private companies to individuals is straightforward, as the CVR register contains ownership shares for each private company and SKAT has a database on stock market transactions carried out by private companies. Thus, a next future step for our paper would be to link private companies and individuals to expand the dataset in terms of transactions. It would furthermore be of interest to combine the trading data with data on convicted criminals, investigating whether the insiders investigated are convicted of doing something illegal.

Conclusion

We were guided by the research question: *"to which extent can it be argued that corporate insiders and their network are in a privileged position compared to the general public prior to the release of corporate announcements?"*. We sought to answer this question by testing the four hypotheses:

> Hypothesis 1: *Insiders' trading activity rises prior to the release of corporate announcements.*
> Hypothesis 2: *Corporate insiders are better at predicting the direction of a significant announcement than outsiders.*
> Hypothesis 3: *Differences in trading patterns are not explained by socioeconomic factors.*
> Hypothesis 4: *Corporate insiders, their network, and family earn higher returns than the overall population prior to company specific announcements.*

To test these four hypotheses we gathered a unique unpublished dataset containing: real time records of all stock transactions of Danish citizens from SKAT, records on corporate insiders (including top-management, board members and accountants) for all listed Danish companies from the CVR-register, all company specific announcements that listed Danish companies are legally obliged to report from the Danish Financial Supervisory Authority, daily price data on all listed Danish companies, and lastly register data from Statistics Denmark. Past research has only succeeded in studying subsets of the insider trading phenomenon as it was limited to using databases on reported insider trades or court data on convicted insider trades. Unlike the data used by previous scholarship, our dataset allows us to study a larger part of the landscape of insider trading in Denmark.

To test hypothesis 1 and 2 we conducted an event study where we compared the trading behaviour of insiders, outsiders, and individuals associated to other listed companies than the one they traded in. We used the event study to investigate how the trading activity of the different groups evolved around corporate announcements. From this analysis, we found that insiders' trading activity is significantly larger than their average trading patterns shortly before the release of corporate announcements, and that this pattern is significantly different from the two other groups' on market level. We thus found evidence for hypothesis 1. Furthermore, we found evidence of hypothesis 2 when we limited the event study to solely contain announcements that had an absolute pricing impact of at least 5%. The direction of insider trades were found to significantly predict the pricing outcome of the corporate announcement as 67.46% (30.91%) of insider trades, executed within 30 days of the release of significant announcements, were purchases when the pricing impact was an increase (decrease). This supports the prediction of hypothesis 2, as no such change in direction of trading was observed for other groups of trades. We therefore failed to reject hypotheses 1 and 2, indicating that corporate insiders trade more and in the right direction prior to corporate announcements.

Hypothesis 3 was tested in order to investigate whether the findings from the event study persisted when controlling for socioeconomic factors such as income, job type, and years of schooling. Similar to the event study we found, running a pooled cross-sectional regression, that the trade size of an average insider transaction increases by 225% when at least one corporate announcement occurs within 30 days of the trade. This coefficient was statistically significant and testifies that corporate insiders trade more on average before announcements: even after controlling for socioeconomic factors.

Lastly, we test hypothesis 4 in order to understand whether increased insider trading activity prior to the release of corporate announcements translates into superior abnormal returns compared to the rest of the population. We find that, in the short term, insider trading abnormal returns equal 17% annualized for a 7-day holding period, and 99% annualized for a one-day holding period. This indicates that insiders trade shortly before substantial changes in returns of their company. In extension, we found that the 30 day abnormal return of family insiders amount to 33% on an annual basis. In comparison to the rest of the population no such returns are observed.

Held together our findings indicate that corporate insiders are at an advantageous position compared to other traders as insiders: trade more prior to corporate announcements, trade in the right direction of the price impact of announcement, and earn higher returns on their trades. The family also earns high abnormal returns. This suggests that corporate insiders and their families are in possession of, and trade on, information that other investors do not possess.

Yet, further work needs to be done in order to cement our findings. Firstly, one should investigate whether the high short term returns earned by corporate insiders is due to trade mimicking or due to release of corporate announcement. This could be tested by investigating the pricing impact of insider trading days on the stock price development. Secondly, future research should link transactions from foreign bank accounts and through private holding companies to corporate insiders. Thirdly, future research should establish further network links and add register data on criminal offenses to explore how many of the potential insiders are caught.

Despite these shortcomings our study has send a strong signal that a subsection Danish corporate insiders and their families appear to outperform the market by trading on non-public information.

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Appendix

Appendix 1: "Buzzwords" Used to Select Announcements

ekstraordinær generalforsamling (extraordinary general assembly)
ekstraordinær indfrielse (extraordinary redemption)
handel (trade)
storaktionærmeddelelse (shareholder announcement)
selskabsmeddelelse (company announcement)
delårsrapport (interim report)
årsrapport (annual report)
halvårsrapport (semiannual report)
aktietilbagekøb (share repurchase)
kvartal (quarter)
indberetning (reporting)
generalforsamling (general assembly)
indfrielse (redemption)
meddelelse (announcement)
ledende (leading)
stemmerettigheder (voting rights)
ordre (order)
sælger (sells)
køber (purchases)

Appendix 2: Personal Characteristics for Insiders for All Sells

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider	in listed	insider	(2) – (1)	(3) – (1)	(3) – (2)
	mean /sd	mean /sd	mean /sd	dif/t	dif/t	dif/t
female	0.38	0.11	0.14	-0.27***	-0.25***	0.02
	0.49	0.32	0.34	[-31.71]	[-7.60]	[1.12]
age	53.42	59.41	51.56	5.99***	-1.91	-7.86***
	18.19	12.41	8.21	[18.71]	[-1.58]	[-9.39]
couple	0.67	0.86	0.89	0.19***	0.22***	0.04
	0.47	0.35	0.31	[22.32]	[7.09]	[1.55]
number of children	1.51	2	2.11	0.49***	0.59***	0.11
	1.16	1	1.03	[23.97]	[7.72]	[1.55]
education length	14.06	15.54	16.2	1.49***	2.13***	0.66***
	2.85	2.5	2.34	[29.26]	[11.12]	[3.79]
financial literacy	0.08	0.31	0.4	0.23***	0.32***	0.09**

	0.27	0.46	0.49	[48.03]	[17.68]	[2.86]
unemployed	0.02	0.01	0	-0.01***	-0.02*	-0.01
	0.13	0.08	0	[-4.56]	[-1.97]	[-1.22]
selfemployed	0.05	0.26	0.5	0.22***	0.45***	0.24***
	0.21	0.44	0.5	[56.86]	[31.45]	[7.68]
works within finance	0.02	0.06	0.09	0.03***	0.07***	0.04*
	0.15	0.23	0.29	[12.10]	[6.69]	[2.19]
works within management	0.04	0.24	0.46	0.20***	0.42***	0.22***
	0.2	0.43	0.5	[55.71]	[30.61]	[7.26]
works within top management	0.01	0.15	0.3	0.14***	0.28***	0.14***
	0.11	0.36	0.46	[69.65]	[37.20]	[5.69]
number of companies	0	1.39	1.56	1.39***	1.55***	0.17*
	0.04	1.08	1.27	[811.28]	[160.81]	[2.28]
individual income	428061.5	2740000	5480000	2.31e+06***	5.03e+06***	2.73e+06*
	1280000	1.7E+07	8560000	[67.25]	[38.74]	[2.36]
annual trade as percentage of income	2.1	5.23	1.76	3.12	-0.37	-3.47
	347.32	116.92	6.2	[0.51]	[-0.02]	[-0.45]
individual wealth	1170000	14000000	10400000	1.28e+07***	9.17e+06***	-3.59E+06
	9200000	2.4E+08	2.8E+07	[32.41]	[6.14]	[-0.22]
average trade as percentage of wealth	-0.28	0.55	-0.66	0.83	-0.39	-1.22
	456.82	19.95	21.57	[0.10]	[-0.01]	[-0.88]
average trade size	51070.48	554219	9340000	503148.55***	9.29e+06***	8.79e+06***
	1700000	7030000	7.7E+07	[16.29]	[79.63]	[6.24]
average trade in company per year	111707.6	1050000	11300000	942149.49***	1.12e+07***	1.03e+07***
	2140000	8570000	7.8E+07	[24.31]	[76.41]	[7.06]
average trade amount per year	284442.8	2140000	13400000	1.86e+06***	1.31e+07***	1.13e+07***
	3980000	1.6E+07	7.9E+07	[25.73]	[47.78]	[6.56]
Observations	498754	3371	232	502125	502125	3603

t statistics in parentheses

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

Appendix 3: Person Characteristics for Insiders for All Buys

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider	in listed	insider	dif 1,2	dif 1,3	dif 2, 3
	mean /sd	mean /sd	mean /sd	dif/t	dif/t	dif/t
female	0.34	0.1	0.15	-0.24***	-0.19***	0.05*
	0.47	0.3	0.35	[-24.79]	[-6.53]	[2.32]
age	50.7	58.89	51.17	8.19***	0.41	-7.72***
	16.73	12.35	8.51	[24.34]	[0.40]	[-9.98]

couple	0.71	0.87	0.93	0.16***	0.22***	0.06**
	0.45	0.34	0.25	[17.13]	[7.90]	[2.97]
number of children	1.47	2	2.02	0.53***	0.54***	0.02
	1.16	1.03	0.98	[22.64]	[7.66]	[0.27]
education length	14.38	15.74	16	1.36***	1.61***	0.26
	2.7	2.46	2.32	[24.65]	[9.65]	[1.65]
financial literacy	0.09	0.32	0.4	0.23***	0.32***	0.09**
	0.28	0.46	0.49	[40.28]	[18.22]	[2.88]
unemployed	0.02	0	0	-0.01***	-0.02*	0
	0.12	0.07	0	[-4.27]	[-2.05]	[-1.14]
selfemployed	0.06	0.29	0.5	0.23***	0.44***	0.21***
	0.23	0.45	0.5	[49.32]	[30.62]	[7.00]
works within finance	0.03	0.06	0.08	0.03***	0.06***	0.03
	0.16	0.23	0.28	[9.01]	[5.78]	[1.84]
works within management	0.05	0.26	0.42	0.21***	0.36***	0.15***
	0.22	0.44	0.49	[47.53]	[26.74]	[5.29]
works within top management	0.02	0.17	0.31	0.16***	0.30***	0.14***
	0.12	0.38	0.47	[60.97]	[38.30]	[5.75]
number of companies	0	1.44	1.64	1.44***	1.63***	0.20**
	0.06	1.12	1.44	[669.67]	[177.60]	[2.81]
individual income	475288.9	2.98E+06	5.77E+06	2.50e+06***	5.28e+06***	2.79e+06**
	1.64E+06	1.41E+07	2.13E+07	[60.22]	[41.80]	[2.91]
annual trade as percentage of income	3.06	7	0.32	3.95	-2.77	-6.68
	410.04	144.69	1.17	[0.48]	[-0.11]	[-0.76]
individual wealth	1.42E+06	1.74E+07	4.02E+07	1.60e+07***	3.87e+07***	2.28E+07
	1.91E+07	3.78E+08	5.31E+08	[20.53]	[16.38]	[0.90]
average trade as percentage of wealth	-0.29	0.57	0.18	0.86	0.46	-0.39
	529.1	17.63	1.33	[0.08]	[0.01]	[-0.37]
average trade size	36171.99	300732.1	1.23E+06	264560.08***	1.19e+06***	927133.39***
	149895	2.78E+06	3.85E+06	[49.08]	[73.26]	[5.05]
average trade in company per year	109511	640547	1.40E+06	531036.07***	1.29e+06***	756901.65*
	1.39E+06	5.42E+06	4.16E+06	[18.43]	[14.74]	[2.26]
average trade amount per year	324357	1.69E+06	2.15E+06	1.36e+06***	1.81e+06***	458599.7
	4.03E+06	1.14E+07	6.94E+06	[16.66]	[7.33]	[0.66]
Observations	381719	2562	278	384281	384281	2840

t statistics in parentheses

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

Appendix 4: Person Characteristics for Family for All Sells

	(1)	(2)	(3)	(4)	(5)	(6)
	not family	family	insider family	dif 1:2	dif 1:3	dif 2:3
	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t
h_female	0.21	0.38	0.42	0.17***	0.21***	0.05
	(0.41)	(0.49)	(0.49)	[79.38]	[10.62]	[1.88]
h_age	53.80	52.95	47.78	-0.86***	-6.01***	-5.16***
	(15.42)	(17.08)	(21.43)	[-10.59]	[-7.93]	[-6.11]
couple	0.71	0.74	0.58	0.04***	-0.13***	-0.17***
	(0.46)	(0.44)	(0.49)	[16.13]	[-5.72]	[-7.69]
h_children_all	1.57	1.74	1.44	0.17***	-0.13*	-0.30***
	(1.16)	(1.29)	(1.31)	[28.12]	[-2.24]	[-4.64]
educlen	14.50	14.94	15.25	0.44***	0.74***	0.31*
	(2.66)	(2.68)	(2.92)	[31.45]	[5.63]	[2.30]
edu_finlit	0.10	0.16	0.18	0.05***	0.07***	0.02
	(0.30)	(0.36)	(0.38)	[34.09]	[4.93]	[1.12]
emp_unemployed	0.02	0.04	0.02	0.01***	0.00	-0.01
	(0.14)	(0.19)	(0.15)	[19.46]	[0.43]	[-1.25]
emp_selfemployed	0.06	0.09	0.05	0.03***	-0.01	-0.04**
	(0.24)	(0.28)	(0.21)	[24.41]	[-1.07]	[-3.00]
dis_financework	0.02	0.03	0.05	0.01***	0.03***	0.02*
	(0.15)	(0.17)	(0.22)	[6.75]	[3.36]	[2.38]
dis_mgmt	0.05	0.08	0.03	0.03***	-0.02	-0.05***
	(0.21)	(0.27)	(0.17)	[27.10]	[-1.58]	[-3.53]
dis_topmgmt	0.01	0.05	0.02	0.04***	0.01	-0.03**
	(0.12)	(0.22)	(0.15)	[59.03]	[1.28]	[-2.66]
antal_virksomheder	0.02	0.09	0.09	0.08***	0.07***	-0.01
	(0.19)	(0.62)	(0.39)	[79.08]	[7.72]	[-0.18]
ind_income	571797.38	1.31e+06	493087.89	735062.17***	-86097.40	-8.14e+05*
	(3.06e+06)	(8.00e+06)	(659592.16)	[44.65]	[-0.56]	[-2.07]
average_perc_inc	34.01	0.56	2.28	-33.45***	-31.40	1.72
	(873.31)	(51.55)	(6.44)	[-7.38]	[-0.74]	[0.68]
ind_wealth	2.08e+06	6.12e+06	7.82e+06	4.04e+06***	5.70e+06***	1.70e+06
	(2.09e+07)	(3.09e+07)	(1.50e+07)	[36.68]	[5.52]	[1.12]
average_perc_wealth	0.34	10.15	0.22	9.81	-0.22	-9.93
	(1165.95)	(145.07)	(1.18)	[1.62]	[-0.00]	[-1.41]
averageTradeSize	100523.81	171687.86	213594.99	71151.25***	112354.26***	41907.13
	(680218.85)	(570292.67)	(1.15e+06)	[20.63]	[3.45]	[1.50]
averageCompanySample	2.42e+06	1.28e+06	702355.70	-1.14e+06***	-1.71e+06**	-5.80e+05*
	(1.14e+07)	(4.73e+06)	(1.57e+06)	[-19.76]	[-3.14]	[-2.56]
averageTradeSample	1.17e+07	5.16e+06	702572.29	-6.58e+06***	-1.10e+07***	-4.45e+06***

	(5.51e+07)	(1.06e+07)	(1.57e+06)	[-23.61]	[-4.17]	[-8.78]
Observations	3850228	39183	436	3889847	3889847	39619

Appendix 5: Person Characteristics for Family for All Sells

	(1)	(2)	(3)	(4)	(5)	(6)
	not family	family	insider family	dif 1:2	dif 1:3	dif 2:3
	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t
h_female	0.19	0.37	0.43	0.17***	0.23***	0.06*
	(0.39)	(0.48)	(0.50)	[87.93]	[10.11]	[2.17]
h_age	53.58	53.32	53.05	-0.26***	-0.53	-0.27
	(15.07)	(16.75)	(20.46)	[-3.48]	[-0.60]	[-0.27]
couple	0.71	0.75	0.67	0.03***	-0.04	-0.07**
	(0.45)	(0.43)	(0.47)	[14.80]	[-1.59]	[-2.94]
h_children_all	1.55	1.74	1.68	0.19***	0.13	-0.06
	(1.16)	(1.30)	(1.23)	[32.52]	[1.90]	[-0.76]
educlen	14.59	14.98	14.76	0.39***	0.16	-0.22
	(2.64)	(2.68)	(2.92)	[29.34]	[1.02]	[-1.40]
edu_finlit	0.10	0.16	0.12	0.06***	0.02	-0.04
	(0.30)	(0.37)	(0.33)	[42.56]	[1.33]	[-1.80]
emp_unemployed	0.02	0.04	0.01	0.02***	-0.01	-0.03*
	(0.14)	(0.20)	(0.12)	[28.04]	[-0.86]	[-2.34]
emp_selfemployed	0.06	0.09	0.04	0.03***	-0.02	-0.05**
	(0.24)	(0.29)	(0.21)	[25.83]	[-1.16]	[-2.77]
dis_financework	0.02	0.03	0.04	0.01***	0.02*	0.01
	(0.14)	(0.16)	(0.19)	[7.62]	[2.01]	[1.22]
dis_mgmt	0.05	0.08	0.04	0.03***	-0.01	-0.04*
	(0.22)	(0.27)	(0.20)	[30.16]	[-0.45]	[-2.38]
dis_topmgmt	0.01	0.05	0.03	0.04***	0.02**	-0.02
	(0.12)	(0.22)	(0.18)	[63.95]	[2.64]	[-1.50]
antal_virksomheder	0.01	0.08	0.05	0.07***	0.04***	-0.03
	(0.18)	(0.58)	(0.35)	[74.52]	[3.91]	[-1.02]
ind_income	580239.93	1.32e+06	1.10e+06	735037.91***	508617.60*	-2.19e+05
	(3.46e+06)	(7.67e+06)	(4.78e+06)	[41.97]	[2.49]	[-0.49]
average_perc_inc	32.40	0.22	2.92	-32.17***	-29.15	2.70
	(856.37)	(56.83)	(15.99)	[-7.62]	[-0.59]	[0.82]
ind_wealth	2.25e+06	7.50e+06	3.02e+07	5.25e+06***	2.79e+07***	2.27e+07***
	(4.55e+07)	(5.74e+07)	(2.12e+08)	[23.14]	[10.54]	[6.50]
average_perc_wealth	1.64	16.34	0.62	14.70**	-1.17	-15.72
	(1134.49)	(288.11)	(2.34)	[2.63]	[-0.02]	[-0.95]
averageTradeSize	81014.71	117462.60	194560.59	36437.45***	113171.71***	77097.99*
	(168767.25)	(612482.87)	(739579.71)	[42.83]	[12.58]	[2.49]

averageCompanySample	2.24e+06	991953.30	287671.13	-1.25e+06***	-1.94e+06***	-7.04e+05***
	(1.07e+07)	(2.46e+06)	(969009.89)	[-24.80]	[-3.64]	[-5.71]
averageTradeSample	1.07e+07	5.00e+06	289003.78	-5.74e+06***	-1.04e+07***	-4.71e+06***
	(5.09e+07)	(9.55e+06)	(968794.61)	[-23.87]	[-4.09]	[-9.83]
Observations	4319377	44802	397	4364576	4364576	45199

Appendix 6: Person Characteristics for Company Network for All Sells

	(1)	(2)	(3)
	company network insider	dif in listed company	dif insider
	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t
h_female	0.25	0.21***	0.13***
	(0.43)	[20.65]	[5.29]
h_age	54.44	-6.48***	3.59***
	(7.90)	[-10.36]	[6.94]
couple	0.95	0.12***	0.02
	(0.22)	[5.95]	[1.30]
h_children_all	1.93	0.07	-0.25***
	(0.80)	[1.10]	[-4.31]
educlen	16.41	0.54***	-0.22
	(1.71)	[4.25]	[-1.62]
edu_finlit	0.57	0.19***	0.15***
	(0.50)	[7.32]	[4.56]
emp_unemployed	0.00	-0.01	0.00
	(0.00)	[-1.41]	[.]
emp_selfemployed	0.57	0.37***	-0.02
	(0.50)	[17.80]	[-0.49]
dis_financework	0.01	-0.03**	-0.04***
	(0.09)	[-2.68]	[-3.32]
dis_mgmt	0.55	0.37***	0.01
	(0.50)	[18.46]	[0.39]
dis_topmgmt	0.46	0.34***	0.07
	(0.50)	[20.11]	[1.93]
antal_virksomheder	3.67	2.14***	2.28***
	(2.72)	[34.92]	[17.31]
ind_income	2.47e+07	2.20e+07***	1.69e+07***
	(3.28e+07)	[25.91]	[10.88]
average_perc_inc	0.54	-123.23***	-0.98***
	(0.72)	[-3.74]	[-4.06]
ind_wealth	3.59e+07	2.43e+07**	2.49e+07***
	(4.76e+07)	[2.85]	[10.32]

average_perc_wealth	0.46	-0.25	1.64
	(1.22)	[-0.06]	[1.26]
averageTradeSize	1.25e+06	732807.04*	-6.17e+06*
	(2.22e+06)	[2.30]	[-2.28]
averageCompanySample	1.50e+07	6.21e+06***	2.12e+06
	(2.57e+07)	[4.20]	[0.71]
averageTradeSample	1.52e+07	-1.65e+07***	2.23e+06
	(2.56e+07)	[-3.91]	[0.75]
Observations	365	40209	895

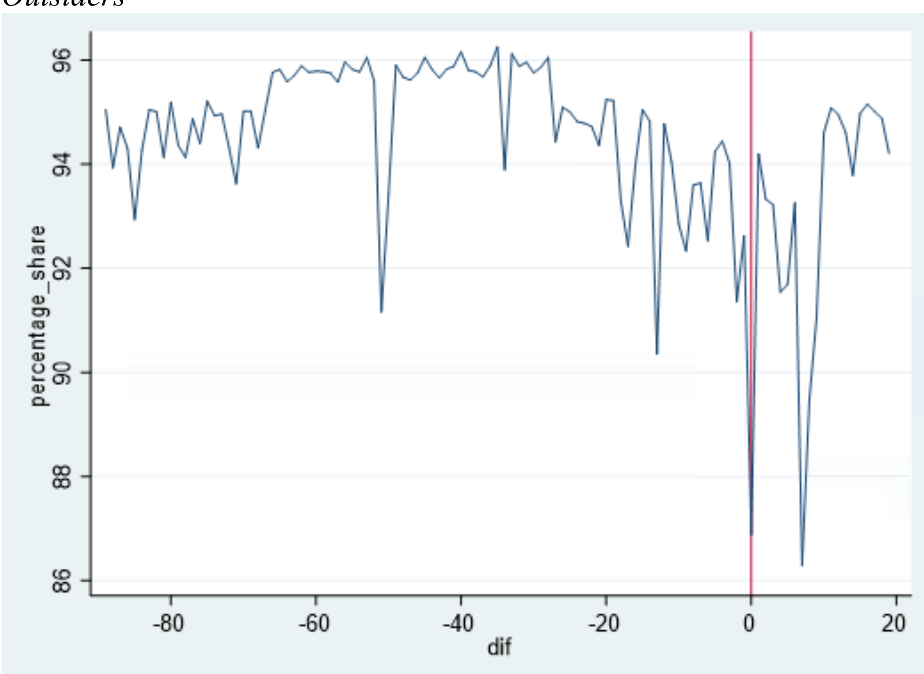
Appendix 7: Person Characteristics for Company Network for All Buys

	(1)	(2)	(3)
	company network insider	dif in listed company	dif insider
	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t
h_female	0.19	0.15***	0.05*
	(0.39)	[16.11]	[2.00]
h_age	53.98	-7.17***	4.07***
	(7.97)	[-12.19]	[7.69]
couple	0.93	0.10***	-0.00
	(0.26)	[5.55]	[-0.15]
h_children_all	1.86	-0.01	-0.23***
	(0.86)	[-0.20]	[-3.93]
educlen	16.54	0.72***	0.52***
	(1.81)	[6.06]	[3.98]
edu_finlit	0.54	0.17***	0.17***
	(0.50)	[7.15]	[5.23]
emp_unemployed	0.00	-0.00	0.00
	(0.00)	[-1.34]	[.]
emp_selfemployed	0.54	0.35***	-0.00
	(0.50)	[17.47]	[-0.03]
dis_financework	0.02	-0.02	-0.07***
	(0.13)	[-1.84]	[-4.74]
dis_mgmt	0.55	0.37***	0.10**
	(0.50)	[19.82]	[2.85]
dis_topmgmt	0.48	0.37***	0.12***
	(0.50)	[23.52]	[3.51]
antal_virksomheder	3.08	1.53***	1.57***
	(2.45)	[26.48]	[12.28]
ind_income	2.30e+07	2.03e+07***	1.53e+07***
	(6.20e+07)	[22.74]	[4.69]

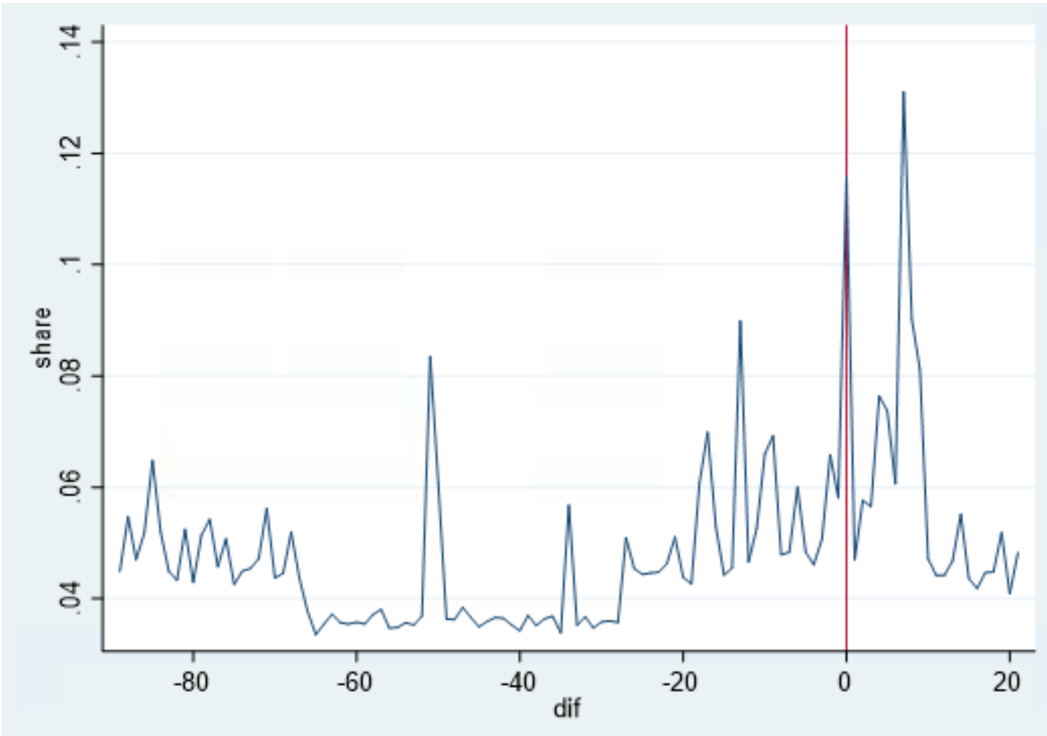
average_perc_inc	0.35	-122.02***	0.06
	(0.79)	[-4.02]	[0.82]
ind_wealth	1.67e+08	1.49e+08***	9.08e+07
	(1.40e+09)	[7.40]	[1.13]
average_perc_wealth	0.26	-0.58	0.00
	(0.65)	[-0.14]	[0.05]
averageTradeSize	804976.00	528677.66***	-8.02e+05*
	(5.77e+06)	[11.59]	[-2.29]
averageCompanySample	2.00e+06	-5.85e+06***	-85254.98
	(6.22e+06)	[-4.53]	[-0.22]
averageTradeSample	4.44e+06	-2.49e+07***	2.13e+06***
	(9.61e+06)	[-6.64]	[3.99]
Observations	424	41573	923

Appendix 8: Outsiders' and "in listed" percentage share of total trade volume

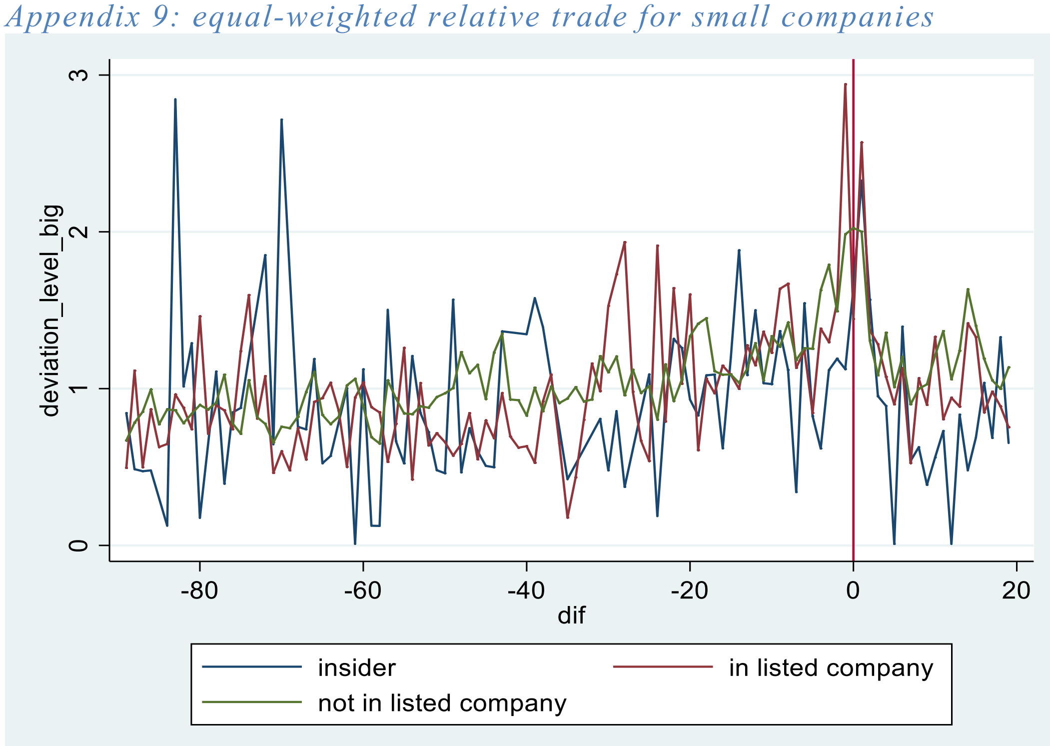
Outsiders



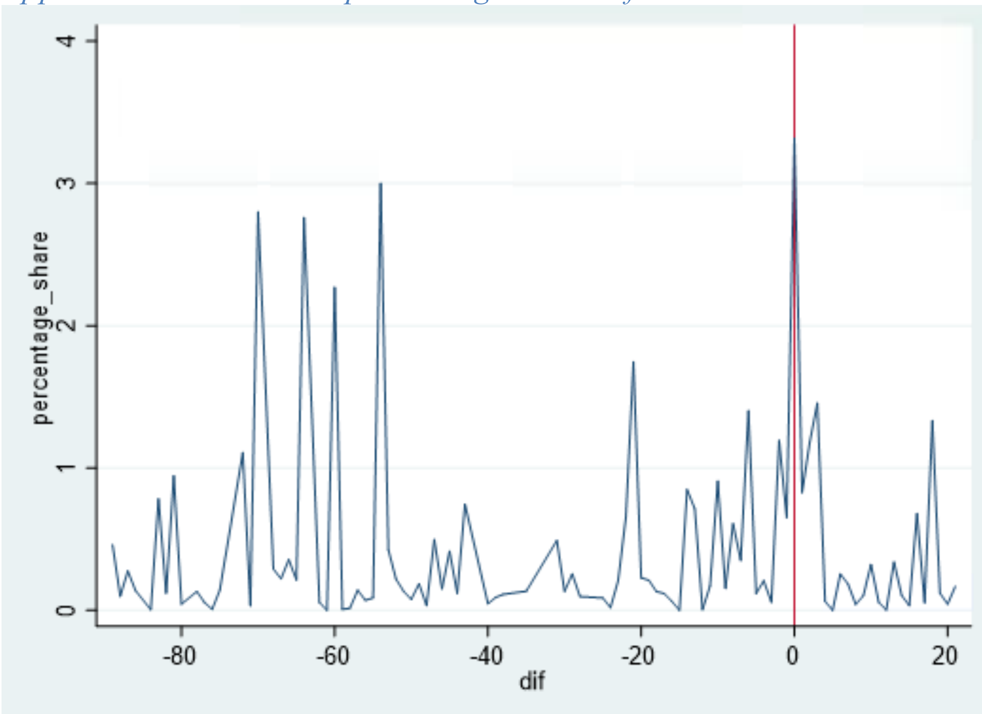
"In listed"



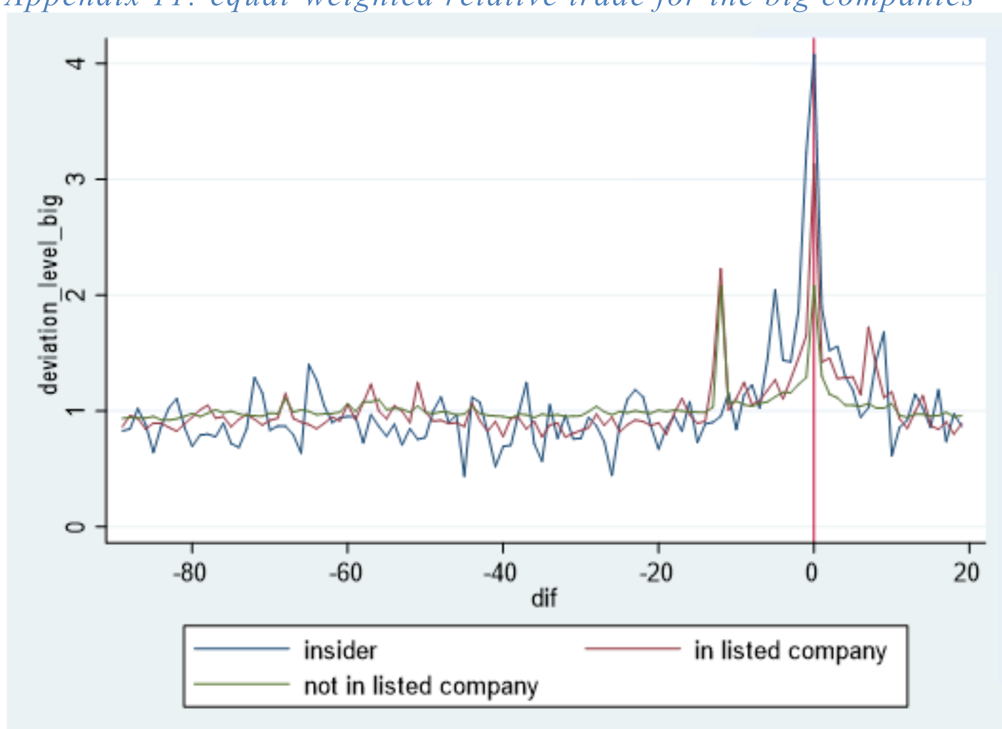
Appendix 9: equal-weighted relative trade for small companies



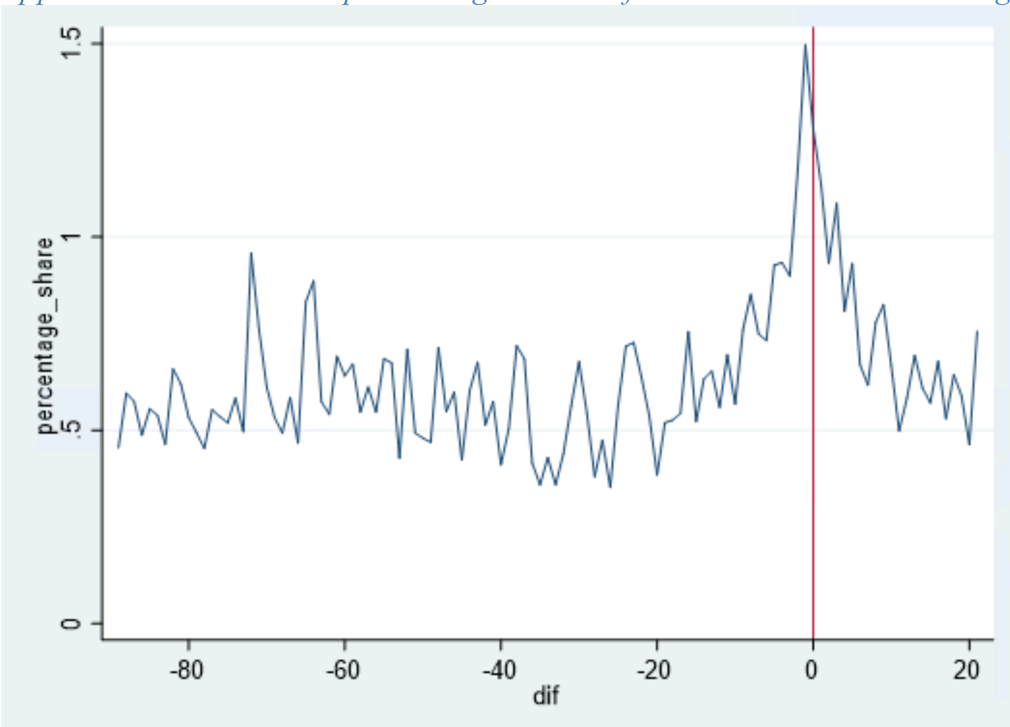
Appendix 10: insiders' percentage share of total trade volume in small companies



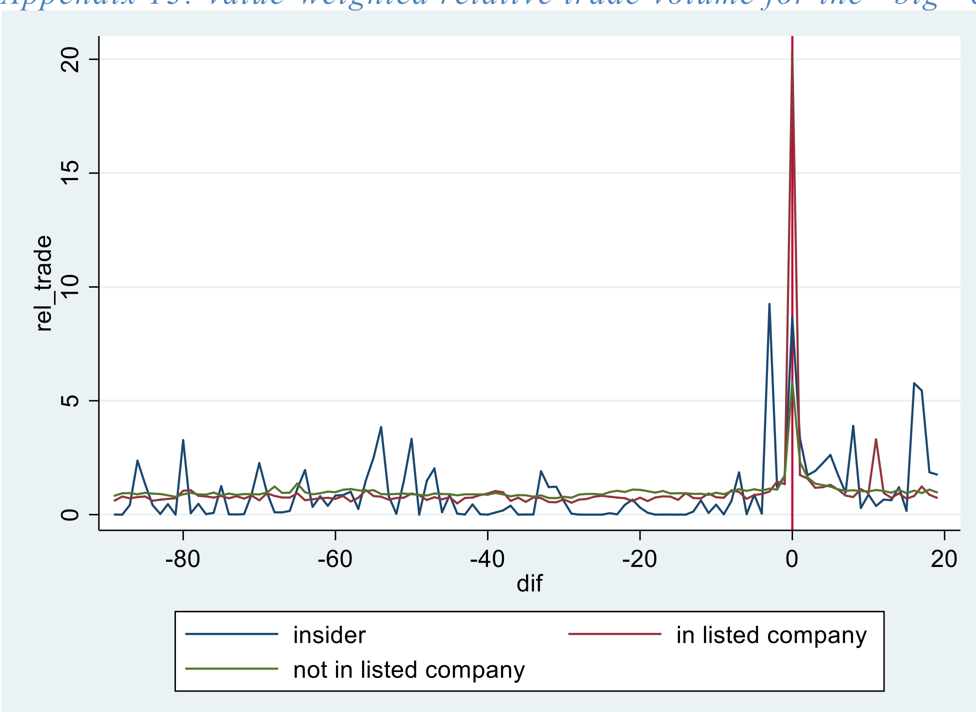
Appendix 11: equal-weighted relative trade for the big companies



Appendix 12: insiders' percentage share of total trade volume in big companies



Appendix 13: value-weighted relative trade volume for the "big" companies



Appendix 14: purchase ratios following a significant announcement

		insiders	in listed	outsiders
price increase	announcement < trade < 21 days	45.34%	40.70%*	48.93%*
price decrease	announcement < trade < 21 days	63.16%*	50.91%	54.40%*

Stars signify statistical significant difference from a purchase ratio of 50% at the 95% level using the t-distribution

Appendix 15: regression results for log and absolute trade value

	Regression output for log trade value			Regression output for absolute trade value		
	(1) short	(2) interaction	(3) w. characteristics	(4) short	(5) interaction	(6) w. characteristics
in listed	0.813***	0.832***	0.479***	77841.2*	-146616.8***	-124263.8***
	82.58	50.97	28.76	2.35	(3.37)	(5.27)
insider	1.616***	-0.286	-0.686**	4247782.6***	-932471.4	-975428.9
	17.3	(1.22)	(2.75)	-3.75	(1.43)	(1.32)
number of companies	0.203***	0.204***	0.108***	148028.7***	148332.6***	124402.1***
	36.94	36.94	17.4	8.41	8.37	9.51
family	0.305***	0.427***	0.464***	37539.8***	40971.9***	35903.5***
	53.53	29.11	31.7	11.57	9.33	7.96
family insider	-0.0692	0.158	0.393**	95417.3**	-85353.4*	-33575.7
	(0.99)	1.04	2.67	2.72	(2.24)	(1.06)
insider company network	0.441***	0.352*	0.401**	191183.1	152787	207461.1
	7.32	2.38	2.66	1.06	0.73	1.07
thirtyD	0.309***	0.310***	0.322***	24658.3***	22667.3***	24336.7***
	220.98	219.38	228.72	53.05	114.92	128.12
minusthirtyD	0.243***	0.244***	0.265***	22876.7***	21118.2***	22745.4***
	177.56	176.09	192.71	49.9	107.38	121.69
thirtyD + insider		1.292***	1.178***		3729932.7**	3646105.2**
		6.12	5.61		3.04	2.84
thirtyD + in listed		-0.0203	-0.0122		146402.2***	80477.9***
		(-1.48)	(-0.86)		3.68	7.82

	Regression output for log trade value		Regression output for absolute trade value	
female+ insider	-0.779***	-0.413*	-3934624.2**	-3845846.6**
	(3.77)	(2.12)	(3.19)	(3.06)
female + in listed	-0.523***	-0.286***	-48124	11269.1
	(14.49)	(8.04)	(0.81)	0.24
thirtyD + female	-0.0836***	-0.0834***	2076.2	5055.7
	(6.03)	(6.14)	0.47	1.19
thirtyD + family insider	-0.185	-0.309*	160896.2**	95752.2*
	(1.30)	(2.22)	3.2	2.43
thirtyD + company network insider	0.126	-0.189	329903.1	121870.8
	0.96	(1.35)	1.49	0.79
minus + insider	1.242***	1.229***	3249991.4**	3250244.0**
	5.21	5.1	2.88	2.69
minus + in listed	0.0162	0.0021	154279.2***	85209.0***
	1.21	0.15	3.8	8.3
minus + female	-0.0727***	-0.0470***	-5618.6	-2181.1
	(5.34)	(3.51)	(1.23)	(0.49)
minus + family insider	-0.132	-0.0123	102397.6*	48450.9
	(0.90)	(0.08)	2.02	1.18
minus + company network insider	0.107	-0.320*	-278921	-533956.2*
	0.71	(2.08)	(1.08)	(2.57)
yearid		-0.0000121***		-1.365***
		(12.30)		(7.81)
sell		0.125***		17185.2***
		110.02		47.11
trade on day of announcement		-0.0657***		-3534.2***
		(119.35)		(40.40)

	Regression output for log trade value			Regression output for absolute trade value		
female			-0.247***			-21021.1***
			(167.74)			(77.96)
number of kids			0.0891***			3651.4***
			120.35			15.6
couple			0.00177			-1841.4*
			1.32			(2.51)
age			0.0254***			1044.4***
			554.79			81.37
income			2.88e-08***			0.0108***
			12.53			10.24
wealth			1.87E-10			0.000184
			0.89			1.37
education length			0.0169***			-1717.5***
			53.43			(9.14)
college educated			0.0290***			8607.7***
			16.85			15.7
financial literacy			0.280***			18303.9***
			145.16			19.74
unemployed			0.0554***			-2454.3***
			13.57			(5.14)
works within finance			0.0395***			-8154.7***
			10.25			(10.88)
works as management			0.220***			26577.6***
			64.92			28.15
works as top-management			0.168***			40056.2***
			27.71			5.44
_cons	9.797***	9.796***	8.131***	50717.9***	53550.1***	7219.7**

	Regression output for log trade value			Regression output for absolute trade value		
	-6721.09	-6665	-1441.8	-80.38	-310.26	-2.74
N	8222972	8222972	7494242	8254423	8254423	7521628
	t statistics in parentheses					
	* p<0.05	** p<0.01	*** p<0.001			

Appendix 16: test for multicollinearity: Variance Inflation Factor (VIF)

	VIFs for log trade value			VIFs for absolute trade value		
	(1)	(2)	(3)	(4)	(5)	(6)
	short	interaction	w. characteristics	short	interaction	w. characteristics
	vif	vif	vif	vif	vif	vif
in listed	2.67	7.85	7.94	2.67	7.83	7.92
insider	1.02	8.48	9.37	1.02	8.5	9.4
number of companies	2.75	2.75	2.78	2.75	2.75	2.78
family	1	6.08	6.08	1	6.07	6.07
family insider	1	5.85	5.37	1	5.88	5.39
insider company network	1.03	6.92	6.99	1.03	6.93	7.01
thirtyD	1.05	1.07	1.08	1.05	1.07	1.08
minusthirtyD	1.05	1.07	1.08	1.05	1.07	1.08
thirtyD + insider		4.94	5.15		4.96	5.17
thirtyD + in listed		4.32	4.32		4.32	4.32
female+ insider		1.18	1.19		1.18	1.19
female + in listed		1.09	1.1		1.09	1.1
thirtyD + female		4.4	4.4		4.41	4.41
thirtyD + family insider		3.35	3.16		3.37	3.18
thirtyD + company network insider		4.66	4.65		4.67	4.66
minus + insider		6.31	6.61		6.33	6.63
minus + in listed		4.18	4.19		4.18	4.19
minus + female		4.29	4.27		4.29	4.27
minus + family insider		3.72	3.28		3.74	3.3
minus + company network insider		4.85	4.85		4.86	4.86
yearid			1.03			1.03
sell			1			1

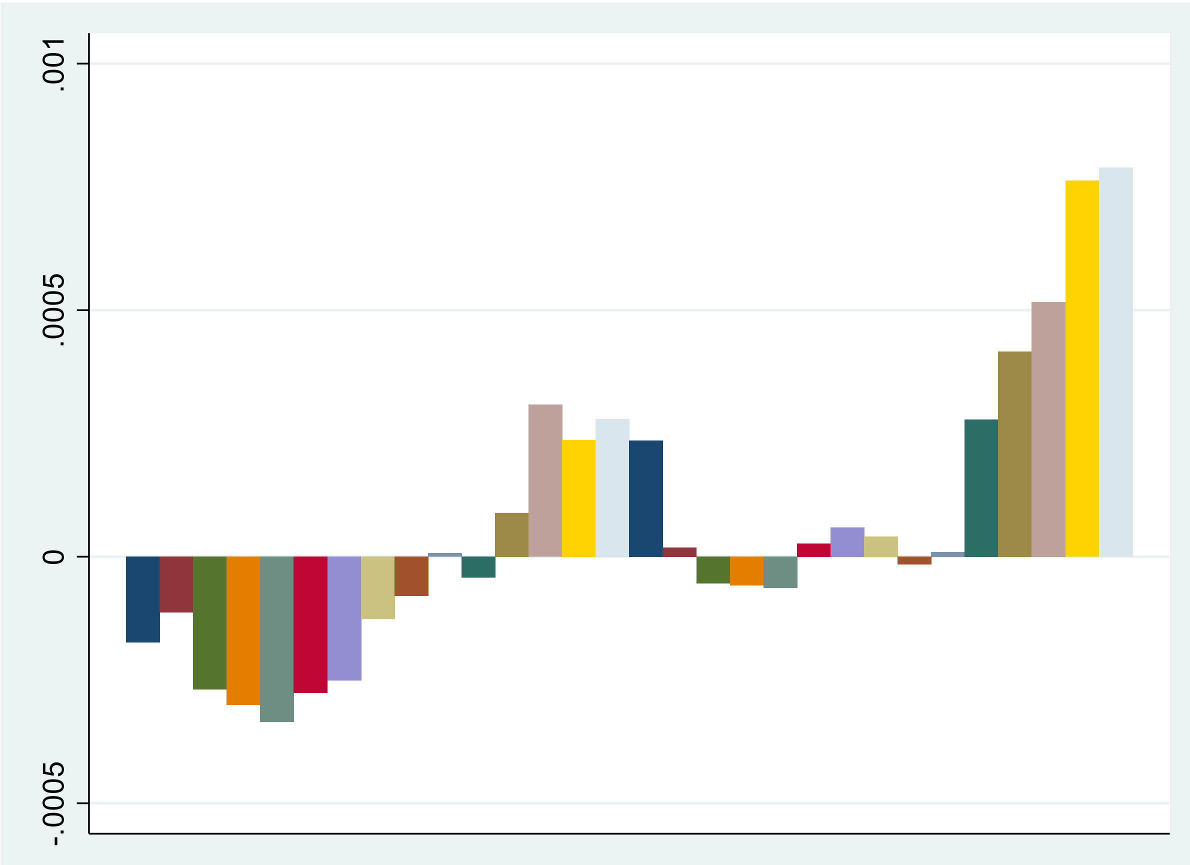
	VIFs for log trade value			VIFs for absolute trade value		
trade on day of announcement			1.02			1.02
female			1.02			1.02
number of kids			1.33			1.33
couple			1.15			1.15
age			1.25			1.25
income			1.41			1.41
wealth			1.39			1.39
education length			2.12			2.12
college educated			2.13			2.13
financial literacy			1.14			1.14
unemployed			1.01			1.01
works within finance			1.08			1.08
works as management			1.44			1.44
works as top-management			1.42			1.42
_cons						
average VIF	1.44625	4.368	3.022222222	1.44625	4.375	3.026388889
N	8222972	8222972	7494242	8254423	8254423	7521628

Appendix 17: tests for heteroscedasticity

	heteroscedasticity test for log trade value			heteroscedasticity test for absolute trade value		
	(1)	(2)	(3)	(4)	(5)	(6)
	short	interaction	w. characteristics	short	interaction	w. characteristics
hettest	2633.4	2722.74	39.66	8.13E+08	1.17E+09	1.10E+10
hetp	0	0	0	0	0	0

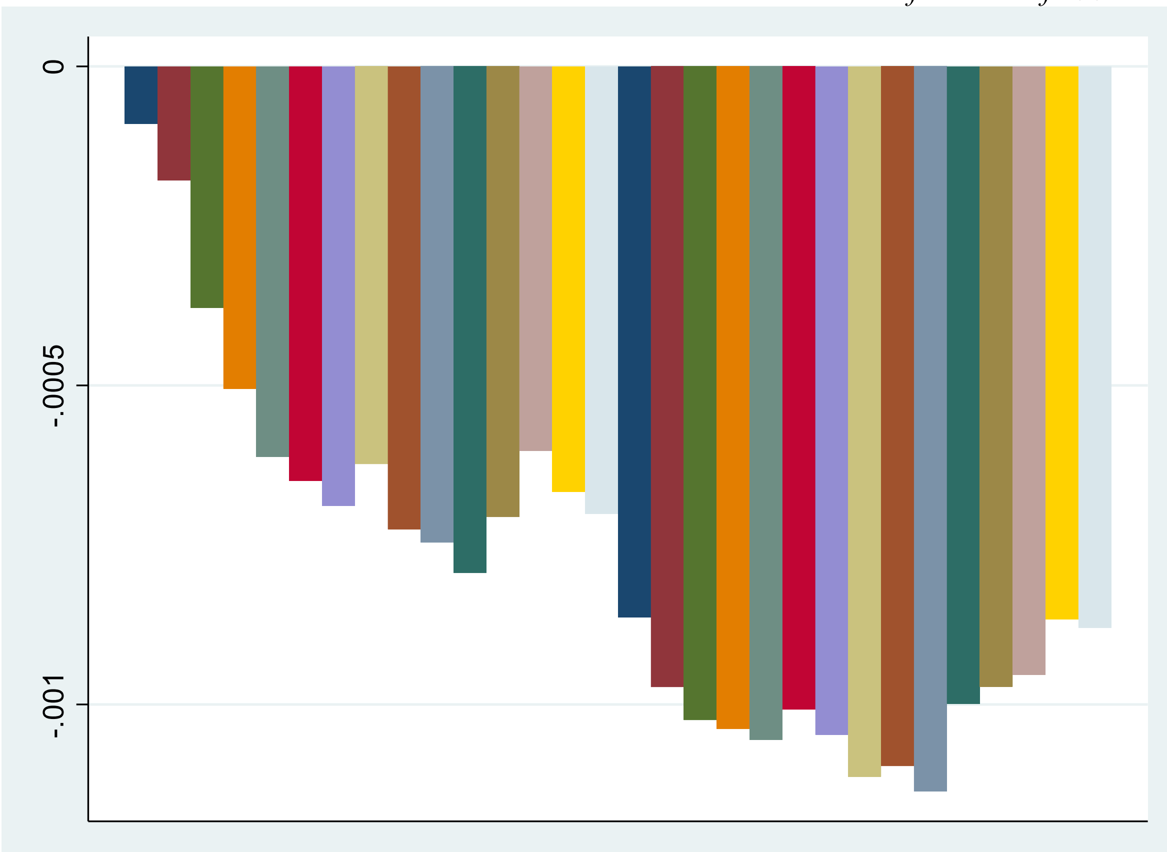
Appendix 18: average absolute returns for the entire population

This figure displays the average absolute returns for 1 through 30 days after a trade for the entire population. The y-axis displays the absolute returns, and the x-axis displays the number of days since the trade



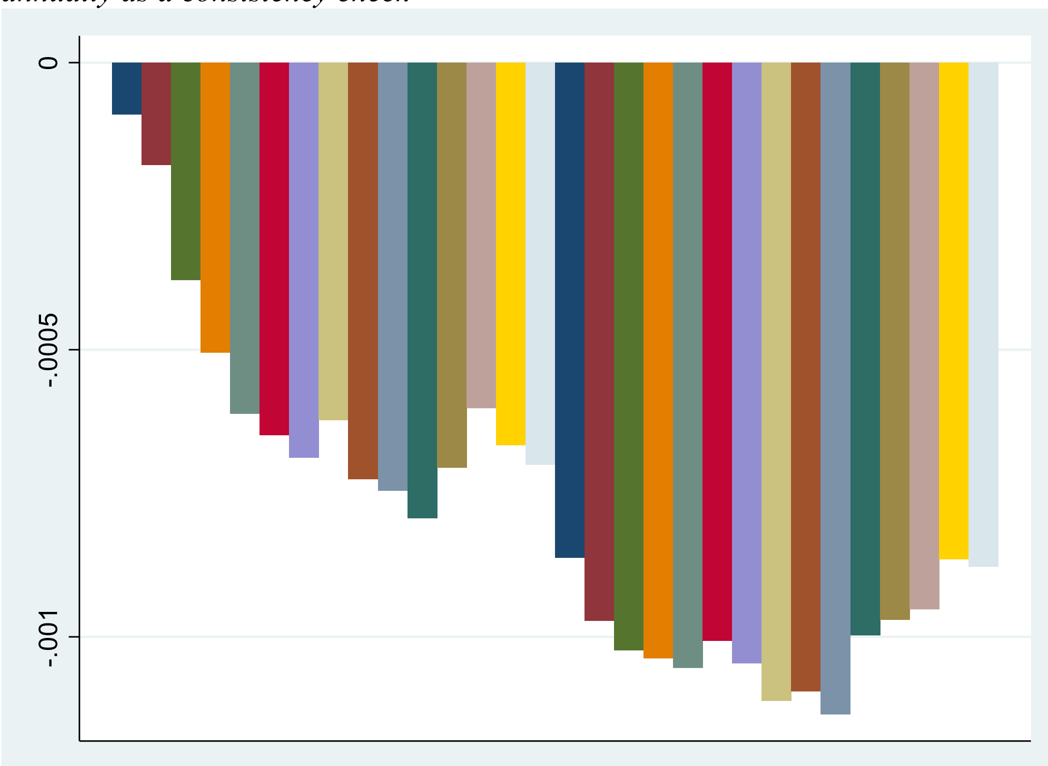
Appendix 19: average abnormal returns for the entire population, rf = 0

This figure displays the average abnormal returns for 1 through 30 days after a trade for the entire population. The y-axis displays the abnormal returns, and the x-axis displays the number of days since the trade. The abnormal returns here are calculated with the base risk free rate of 0% annually



Appendix 20: average abnormal returns for the entire population, rf = 1%

Consistency check. This figure displays the average abnormal returns for 1 through 30 days after a trade for the entire population. The y-axis displays the abnormal returns, and the x-axis displays the number of days since the trade. The abnormal returns here are calculated with a risk free rate of 1% annually as a consistency check



Appendix 21: absolute and abnormal returns for insiders

Significant values in bold

	absolute returns for insiders				abnormal returns for insiders			
	no restriction		30d = 1		no restriction		30d = 1	
days	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	**0.00193391**	**2.0258597**	**0.0025541**	**2.2443142**	0.00168725	1.8332093	**0.00274767**	**2.4844662**
2	**0.00234434**	**2.1022331**	**0.00340706**	**2.5996136**	0.00181739	1.6947248	**0.00311702**	**2.4584327**
3	**0.00307755**	**2.4956274**	**0.00408973**	**2.8509277**	0.00170042	1.466751	**0.00284562**	**2.1089057**
4	**0.00362755**	**2.7155633**	**0.00494459**	**3.1772401**	0.00154684	1.261223	**0.00305593**	**2.1187243**
5	**0.00391057**	**2.7408641**	**0.00440502**	**2.625777**	0.0018637	1.4307052	0.00292982	1.880153
6	**0.00457382**	**2.7921454**	**0.00486932**	**2.4801389**	0.00274621	1.7993036	0.00350073	1.8831564
7	**0.00475572**	**2.8446072**	**0.0058407**	**2.9472883**	0.00300292	1.949025	**0.00440428**	**2.4060425**
8	**0.00422162**	**2.4298035**	**0.00427803**	**2.0481054**	0.00258451	1.6157417	0.00292813	1.5125877
9	**0.00419826**	**2.2917624**	0.00436891	1.9995491	0.00238556	1.4100388	0.00284709	1.3898326
10	**0.00397246**	**2.1478505**	**0.00451393**	**2.0840792**	0.00231563	1.3770248	0.00353289	1.7623433
11	0.00368813	1.8060287	0.00349798	1.4394839	0.00202475	1.0736621	0.00288118	1.2629189
12	0.00375374	1.6863014	0.00343315	1.3052995	0.00164127	0.79225447	0.0023771	0.95975262
13	**0.00486607**	**2.1468176**	0.00430317	1.6131581	0.00257652	1.222857	0.00292254	1.1649374
14	**0.00525371**	**2.2049**	0.00515805	1.8502933	0.0029145	1.3109195	0.00386447	1.4717267
15	**0.00532333**	**2.1415529**	0.00510236	1.73206	0.00305207	1.3248671	0.00407459	1.4732004
16	0.00456165	1.7908699	0.0043818	1.4686949	0.00278492	1.1872386	0.003916	1.4055895
17	0.00410116	1.5412657	0.00373499	1.2021147	0.00254115	1.0202474	0.00340323	1.1572764
18	0.00403187	1.4820614	0.00293169	0.92678505	0.00279491	1.0921971	0.00293961	0.9751611
19	0.00427043	1.4597017	0.00304966	0.8892489	0.00296337	1.0696338	0.00326371	0.98760909
20	**0.00619747**	**2.0211376**	0.00498123	1.3770851	0.00445514	1.5205344	0.00488774	1.3870174
21	**0.00709062**	**2.3138913**	0.00489711	1.3791383	0.00496903	1.6988438	0.00443862	1.2865783
22	**0.0066947**	**2.1250705**	0.00458014	1.2778396	0.00394436	1.3153687	0.00338949	0.9782606
23	**0.00666898**	**2.0277148**	0.0044272	1.1594372	0.00408958	1.3063948	0.00383298	1.0378987
24	0.0048204	1.4497429	0.00329782	0.8577021	0.00239879	0.75606906	0.00287023	0.77053937
25	0.00537702	1.5970129	0.0033116	0.85323841	0.00299419	0.93293495	0.00291303	0.77491031
26	**0.00706232**	**2.0931593**	0.00459805	1.1825897	0.00481163	1.4925382	0.00433186	1.148134
27	0.00551738	1.6541787	0.00332916	0.87268198	0.00346707	1.0905395	0.00337415	0.91675176
28	0.00430019	1.2511776	0.00246217	0.62047728	0.0025365	0.77127014	0.00269169	0.70189186
29	0.0047964	1.3796182	0.00311727	0.76971317	0.00282237	0.85005323	0.00270982	0.6959772
30	0.0054045	1.5364446	0.00293951	0.72083684	0.00327817	0.97079664	0.00269742	0.68237767

Appendix 22: absolute and abnormal returns for family insiders

Significant values in bold

	absolute returns for insider family				abnormal returns for insider family			
	no restriction		thirtyD == 1		no restriction		thirtyD == 1	
days	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	0.00183271	1.3904832	0.00145834	0.99975571	0.00221332	1.7216824	0.00110803	0.77313201
2	0.00133764	0.78701083	0.00164377	0.77339949	0.00080392	0.48590991	0.00020908	0.09932712
3	-0.0022218	-0.58220998	-0.00261492	-0.48522334	-0.00303158	-0.77390683	-0.00455294	-0.8172814
4	-0.00451522	-0.96764579	-0.00615978	-0.92087183	-0.00548793	-1.1406302	-0.00845958	-1.2206735
5	-0.00278704	-0.56563058	-0.00209994	-0.29955371	-0.00407667	-0.80493829	-0.00479099	-0.66156635
6	-0.00170947	-0.33963518	-0.00241025	-0.3366493	-0.00325841	-0.62811723	-0.00507065	-0.68445039
7	-0.00011274	-0.02618296	0.00020392	0.03420329	-0.00164366	-0.37386723	-0.00239045	-0.39115098
8	0.00232073	0.53390618	0.00306133	0.51325912	0.00074405	0.16776775	0.00024301	0.03983526
9	0.00335879	0.76062334	0.00614787	1.0507453	0.00212962	0.47292147	0.00367692	0.61415116
10	0.00323249	0.76330079	0.0085276	1.5732282	0.00208453	0.48617663	0.00575086	1.0465376
11	0.00541691	1.3544948	**0.01039037**	**2.0009583**	0.00448341	1.1238576	0.00743903	1.4226142
12	0.00547264	1.3525193	**0.01143969**	**2.1824625**	0.00410434	1.029392	0.00780763	1.4843911
13	0.00740403	1.8968969	**0.01330202**	**2.7006269**	0.00546571	1.4234944	0.00893709	1.8098611
14	0.00795731	1.9651701	**0.01495265**	**2.9318433**	0.00565396	1.4186749	0.00995266	1.9516824
15	0.00849519	1.9651551	**0.01756804**	**3.1224451**	0.00622227	1.455404	**0.01266382**	**2.2382577**
16	**0.00930017**	**2.0571672**	**0.0175751**	**2.9617561**	0.00730078	1.6359185	**0.01321118**	**2.2261132**
17	0.00912946	1.8399814	**0.0188465**	**2.8535265**	0.00659307	1.3475611	**0.01361329**	**2.05617**
18	0.00812298	1.6136318	**0.01842832**	**2.7443043**	0.00584753	1.184408	0.01322966	1.9764236
19	**0.01036032**	**2.1429974**	**0.02150569**	**3.3607557**	0.00796002	1.6960971	**0.01629346**	**2.5760904**
20	**0.01189555**	**2.2746171**	**0.02284004**	**3.4032817**	0.00954385	1.8772178	**0.01700102**	**2.5735979**
21	**0.01381158**	**2.6498712**	**0.02468228**	**3.7348038**	**0.01085142**	**2.1463181**	**0.01795797**	**2.7698818**
22	**0.01481542**	**2.7619727**	**0.0251151**	**3.6525505**	**0.0115661**	**2.2154482**	**0.01819696**	**2.6871281**
23	**0.0146058**	**2.6886457**	**0.02630968**	**3.7928987**	**0.01119254**	**2.1188255**	**0.01915139**	**2.8074455**
24	**0.01636893**	**2.9617272**	**0.02992521**	**4.2525091**	**0.01240479**	**2.3053733**	**0.02184006**	**3.144706**
25	**0.01998652**	**3.1329821**	**0.03262204**	**4.0858453**	**0.01609013**	**2.5485177**	**0.0244992**	**3.0683648**
26	**0.01631555**	**2.5980712**	**0.02851311**	**3.7423809**	**0.01257723**	**2.0354888**	**0.02044918**	**2.7117517**
27	**0.01684777**	**2.6092465**	**0.02958235**	**3.6964941**	**0.01331096**	**2.0896891**	**0.02183448**	**2.7459638**
28	**0.01423329**	**2.2113694**	**0.02674208**	**3.422451**	0.01112122	1.754369	**0.01925437**	**2.4901823**
29	**0.01526118**	**2.4193777**	**0.02753119**	**3.6243566**	**0.01252366**	**2.0200513**	**0.02083407**	**2.7864045**
30	**0.01816789**	**2.6829346**	**0.02958271**	**3.8245118**	**0.0163125**	**2.4338966**	**0.02382974**	**3.1261129**

Appendix 23: absolute and abnormal returns for family

Significant values in bold

	absolute returns for family				abnormal returns for family			
	no restriction		thirtyD == 1		no restriction		thirtyD == 1	
days	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	-0.00001214	-0.12410444	-0.00011169	-1.0423931	-0.00002228	-0.25485726	-0.00003437	-0.36636192
2	0.00011991	0.89106152	-0.00007386	-0.49025382	-0.00004648	-0.38660592	-0.00016455	-1.2411147
3	0.00005733	0.35901761	-0.00027427	-1.5342218	-0.00021616	-1.5180409	**-0.00045702**	**-2.9107439**
4	0.00011508	0.65106014	-0.00024145	-1.2058783	-0.00025887	-1.6560738	**-0.00055775**	**-3.1921111**
5	-0.0000281	-0.1419632	-0.00033345	-1.483865	**-0.0004534**	**-2.5786874**	**-0.00076331**	**-3.8673596**
6	0.00022816	1.0771359	-0.00003127	-0.13005054	-0.00037271	-1.9757382	**-0.00066244**	**-3.1367656**
7	0.00031881	1.3865229	0.00013467	0.51136031	**-0.00042233**	**-2.066023**	**-0.00065338**	**-2.8333866**
8	0.00043318	1.7755423	0.00026437	0.95283242	-0.00041641	-1.9282204	**-0.00068264**	**-2.8306622**
9	0.00048487	1.8774829	0.00032379	1.0976654	**-0.00054514**	**-2.3736744**	**-0.00082417**	**-3.1919215**
10	**0.00064966**	**2.3963464**	0.00044981	1.437861	**-0.00054954**	**-2.2817276**	**-0.00082432**	**-3.0119522**
11	**0.00071949**	**2.5194817**	0.00032543	0.98328085	**-0.00057416**	**-2.2616001**	**-0.00105725**	**-3.6450958**
12	**0.00086835**	**2.8293637**	0.00059767	1.7028931	-0.00050242	-1.8338359	**-0.00088861**	**-2.8920605**
13	**0.00127771**	**4.0246548**	**0.00110312**	**3.0350531**	-0.00014387	-0.50927764	-0.00048891	-1.5423171
14	**0.00116665**	**3.6195157**	**0.00097065**	**2.6062346**	-0.00011806	-0.41530982	-0.00050766	-1.577398
15	**0.00116927**	**3.5220914**	**0.0010108**	**2.6346921**	-0.00017585	-0.59989486	-0.00055928	-1.686874
16	**0.00123361**	**3.6171331**	**0.00111127**	**2.8229532**	-0.00026971	-0.89543493	-0.00065274	-1.9238086
17	**0.00123589**	**3.5186996**	**0.00102791**	**2.5302899**	-0.00022024	-0.7110778	-0.00063835	-1.8251273
18	**0.00122785**	**3.4247637**	**0.00108184**	**2.6003421**	-0.00022837	-0.72629674	-0.0006124	-1.7170691
19	**0.00121524**	**3.3219563**	**0.00108852**	**2.5632542**	-0.00023789	-0.74295678	-0.00058887	-1.6196895
20	**0.00119488**	**3.2027454**	**0.00101805**	**2.3521818**	-0.00022321	-0.68453021	-0.00061296	-1.6523506
21	**0.00138371**	**3.6295125**	**0.00109373**	**2.4836832**	-0.00009296	-0.2790859	-0.00059937	-1.5840327
22	**0.00152789**	**3.9142072**	**0.00127431**	**2.830087**	-0.00016136	-0.47478755	-0.00066297	-1.7163485
23	**0.0017341**	**4.3584817**	**0.00148365**	**3.235336**	-0.0000886	-0.25493657	-0.00063582	-1.6109377
24	**0.00176639**	**4.3273716**	**0.00155244**	**3.3128038**	-0.00011001	-0.30844033	-0.00062589	-1.5555195
25	**0.00179422**	**4.3119319**	**0.0016343**	**3.422767**	-0.00011199	-0.30752825	-0.00055949	-1.3647652
26	**0.00214471**	**5.0528521**	**0.00201634**	**4.1454932**	0.00006337	0.17085442	-0.00035575	-0.85324101
27	**0.00227754**	**5.2912151**	**0.00205846**	**4.1831504**	0.00016234	0.43205725	-0.00029638	-0.70381086
28	**0.00228899**	**5.2279026**	**0.00201504**	**4.0369305**	0.00014542	0.38022774	-0.00034413	-0.80533988
29	**0.00264812**	**5.9560674**	**0.00237509**	**4.6990668**	0.00033306	0.85787563	-0.00011254	-0.25991714
30	**0.00253528**	**5.6209177**	**0.00211679**	**4.1349043**	0.00030114	0.76401659	-0.00021053	-0.48040208

Appendix 24: absolute and abnormal returns for company network insiders
Significant values in bold

	absolute returns for insider company network				abnormal returns for insider company network			
	no restriction		thirtyD == 1		no restriction		thirtyD == 1	
days	mean	t-stat	mean	t-stat	mean	t-stat	mean	t-stat
1	-0.00023511	-0.22967179	0.00022409	0.18738521	-0.00076635	-0.8275512	0.00009334	0.08797872
2	0.00034524	0.28286902	0.00028547	0.20187752	-0.00034379	-0.34216503	0.00050754	0.44561622
3	0.00061429	0.4311203	0.00045064	0.27500094	-0.00040898	-0.34340885	0.00044754	0.33479683
4	0.00056023	0.36036724	0.00109687	0.61170467	-0.00106291	-0.84409744	0.00053167	0.36794611
5	0.00019125	0.10994712	0.00133765	0.69387114	-0.0016154	-1.1271734	0.00026505	0.16852452
6	0.00145396	0.80063296	0.00292866	1.400643	-0.00101727	-0.67777319	0.00074227	0.43034871
7	0.00217967	1.0987837	0.00406194	1.7555105	-0.00034754	-0.2079519	0.0015258	0.77819383
8	0.00227172	1.077132	0.00375967	1.5228705	-0.00042679	-0.24432727	0.00120076	0.58497275
9	0.00161225	0.71025539	0.00319484	1.2133104	-0.00133216	-0.71890742	0.00048691	0.22714867
10	0.00117973	0.4824825	0.00232659	0.81559201	-0.00211624	-1.0667391	-0.00031777	-0.13821741
11	0.00126411	0.50551926	0.00212458	0.7328105	-0.00192543	-0.95237061	-0.00045498	-0.19481454
12	0.00096022	0.36759957	0.00191576	0.63282644	-0.00216282	-0.99746518	-0.00093858	-0.37721224
13	0.00159957	0.60400347	0.00233283	0.76176055	-0.00181626	-0.82463096	-0.00102001	-0.40105813
14	0.00130184	0.47280555	0.00245986	0.77012929	-0.00234644	-1.0406117	-0.0013132	-0.50323984
15	0.00200267	0.70949244	0.00351668	1.0677369	-0.00211802	-0.90624664	-0.00060093	-0.2205484
16	0.00248837	0.83849466	0.00433553	1.248792	-0.00202318	-0.82047661	-0.0001709	-0.05926693
17	0.00179196	0.59786716	0.00258897	0.73639152	-0.00164969	-0.66414052	-0.00058596	-0.20181148
18	0.00078698	0.25094935	0.00178445	0.48168724	-0.00249311	-0.96393626	-0.00128035	-0.42215258
19	0.00145472	0.44169826	0.00111752	0.28838579	-0.00150018	-0.54781641	-0.00116868	-0.3649043
20	0.0025928	0.76684474	0.00235218	0.59151227	-0.00088213	-0.31581986	-0.0003049	-0.09241097
21	0.00275137	0.78871862	0.00251327	0.61375887	-0.00114121	-0.39400271	-0.00060228	-0.17560655
22	0.0028868	0.78638834	0.00296072	0.6962449	-0.0011924	-0.39124716	-0.00048627	-0.13486458
23	0.00315329	0.86057169	0.00352651	0.82722651	-0.00055717	-0.17992958	0.00020569	0.05607756
24	0.00367746	1.0131088	0.00348822	0.83002262	0.00025929	0.08462145	0.00085073	0.23504132
25	0.00256691	0.70324594	0.00270274	0.63565419	-0.0008179	-0.26474526	0.00054735	0.1517409
26	0.00377247	1.000366	0.00299805	0.6827537	0.00008708	0.02750737	0.00078697	0.21236433
27	0.00390457	1.03426	0.00313823	0.71598042	0.00010931	0.03428745	0.00053783	0.14455808
28	0.00282689	0.73578818	0.00155903	0.35139369	-0.00093686	-0.28881622	-0.00085904	-0.228536
29	0.00319946	0.80674623	0.00241728	0.52664626	-0.00047757	-0.14258317	-0.00014445	-0.03716131
30	0.00282647	0.70842104	0.001588	0.34214083	-0.00140258	-0.413858	-0.00134054	-0.33947955

Appendix 25: absolute returns conditional on 30d = 1

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider mean /sd	in listed mean /sd	insider mean /sd	(2) – (1) dif/t	(3) – (1) dif/t	(3) – (2) dif/t
PercentReturn1	-0.0002	0.0001	0.0026	0.0003*	0.0027*	0.0025*
	0.03	0.03	0.03	[2.16]	[2.41]	[2.32]
PercentReturn2	-0.0002	0.0004	0.0034	0.0005**	0.0036*	0.0031*
	0.04	0.04	0.03	[2.95]	[2.32]	[2.15]
PercentReturn3	-0.0004	0.0002	0.0041	0.0006**	0.0045*	0.0039*
	0.05	0.04	0.04	[2.91]	[2.50]	[2.43]
PercentReturn4	-0.0005	0.0002	0.0049	0.0007**	0.0054**	0.0047*
	0.05	0.05	0.04	[2.88]	[2.65]	[2.57]
PercentReturn5	-0.0005	0.0002	0.0044	0.0006*	0.0049*	0.0042*
	0.06	0.05	0.04	[2.49]	[2.15]	[2.13]
PercentReturn6	-0.0003	0.0002	0.0049	0.0005	0.0052*	0.0047*
	0.07	0.06	0.05	[1.86]	[2.11]	[2.18]
PercentReturn7	-0.0003	0.0005	0.0058	0.0007*	0.0061*	0.0054*
	0.07	0.06	0.05	[2.38]	[2.32]	[2.33]
PercentReturn8	-0.0001	0.0006	0.0043	0.0008*	0.0044	0.0036
	0.07	0.07	0.06	[2.47]	[1.60]	[1.48]
PercentReturn9	-0.0001	0.0009	0.0044	0.0010**	0.0044	0.0035
	0.08	0.07	0.06	[2.96]	[1.53]	[1.32]
PercentReturn10	0	0.0011	0.0045	0.0010**	0.0045	0.0034
	0.08	0.07	0.06	[3.02]	[1.46]	[1.23]
PercentReturn11	-0.0001	0.001	0.0035	0.0011**	0.0036	0.0025
	0.09	0.08	0.06	[2.93]	[1.12]	[0.85]
PercentReturn12	0.0001	0.0009	0.0034	0.0008*	0.0033	0.0025
	0.09	0.08	0.07	[2.13]	[0.99]	[0.81]
PercentReturn13	0.0005	0.0013	0.0043	0.0009*	0.0039	0.003
	0.09	0.09	0.07	[2.17]	[1.12]	[0.93]
PercentReturn14	0.0004	0.0011	0.0052	0.0007	0.0048	0.004
	0.09	0.09	0.07	[1.79]	[1.34]	[1.22]
PercentReturn15	0.0004	0.001	0.0051	0.0005	0.0047	0.0041
	0.1	0.09	0.08	[1.30]	[1.27]	[1.20]
PercentReturn16	0.0004	0.0009	0.0044	0.0006	0.004	0.0034
	0.1	0.1	0.08	[1.32]	[1.05]	[0.96]
PercentReturn17	0.0001	0.0006	0.0037	0.0005	0.0036	0.0031
	0.1	0.1	0.08	[1.18]	[0.93]	[0.85]
PercentReturn18	0	0.0007	0.0029	0.0006	0.0029	0.0023
	0.11	0.1	0.08	[1.37]	[0.72]	[0.60]

PercentReturn19	-0.0001	0.0004	0.003	0.0005	0.0031	0.0026
	0.11	0.11	0.09	[1.06]	[0.75]	[0.65]
PercentReturn20	-0.0001	0.0004	0.005	0.0006	0.0051	0.0045
	0.11	0.11	0.1	[1.18]	[1.21]	[1.08]
PercentReturn21	-0.0001	0.0004	0.0049	0.0005	0.005	0.0045
	0.12	0.11	0.09	[0.92]	[1.15]	[1.08]
PercentReturn22	0	0.0006	0.0046	0.0007	0.0046	0.004
	0.12	0.11	0.1	[1.32]	[1.05]	[0.94]
PercentReturn23	0	0.0007	0.0044	0.0007	0.0044	0.0037
	0.12	0.11	0.1	[1.40]	[0.98]	[0.85]
PercentReturn24	0.0001	0.0007	0.0033	0.0006	0.0032	0.0026
	0.12	0.12	0.1	[1.17]	[0.71]	[0.59]
PercentReturn25	0.0001	0.0006	0.0033	0.0004	0.0032	0.0027
	0.12	0.12	0.1	[0.80]	[0.68]	[0.61]
PercentReturn26	0.0004	0.0009	0.0046	0.0005	0.0042	0.0037
	0.13	0.12	0.1	[0.84]	[0.88]	[0.81]
PercentReturn27	0.0006	0.0011	0.0033	0.0005	0.0027	0.0023
	0.13	0.12	0.1	[0.84]	[0.56]	[0.49]
PercentReturn28	0.0007	0.001	0.0025	0.0003	0.0017	0.0014
	0.13	0.13	0.11	[0.59]	[0.35]	[0.30]
PercentReturn29	0.0009	0.0014	0.0031	0.0005	0.0022	0.0018
	0.13	0.13	0.11	[0.80]	[0.44]	[0.37]
PercentReturn30	0.0008	0.0011	0.0029	0.0003	0.0021	0.0018
	0.14	0.13	0.11	[0.46]	[0.41]	[0.38]
Observations	5744057	55494	713	5799551	5744770	56207

Appendix 26: absolute returns conditional on 30d = 0

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	outsider mean /sd	in listed mean /sd	insider mean /sd	(2) – (1) dif/t	(3) – (1) dif/t	(3) – (2) dif/t
PercentReturn1	-0.0001	0.0004	-0.0001	0.0005*	0.0001	-0.0004
	0.03	0.03	0.02	[2.03]	[0.02]	[-0.22]
PercentReturn2	0	0.0007	-0.0011	0.0007*	-0.0012	-0.0019
	0.05	0.04	0.03	[2.22]	[-0.37]	[-0.69]
PercentReturn3	0.0001	0.0012	-0.0002	0.0011**	-0.0003	-0.0014
	0.05	0.06	0.04	[2.78]	[-0.09]	[-0.37]
PercentReturn4	0.0001	0.001	-0.0007	0.0008*	-0.0008	-0.0017
	0.06	0.06	0.04	[1.98]	[-0.21]	[-0.40]
PercentReturn5	0	0.0009	0.0023	0.0008	0.0023	0.0014
	0.06	0.06	0.04	[1.83]	[0.52]	[0.36]

PercentReturn6	-0.0002	0.0005	0.0036	0.0007	0.0038	0.0031
	0.07	0.07	0.04	[1.47]	[0.81]	[0.66]
PercentReturn7	-0.0003	0.0003	0.0012	0.0006	0.0015	0.0009
	0.07	0.07	0.04	[1.11]	[0.29]	[0.18]
PercentReturn8	-0.0002	0.0004	0.004	0.0006	0.0042	0.0036
	0.08	0.08	0.04	[1.06]	[0.81]	[0.68]
PercentReturn9	-0.0002	0.0005	0.0036	0.0007	0.0038	0.0031
	0.08	0.08	0.05	[1.13]	[0.69]	[0.58]
PercentReturn10	-0.0002	0.0006	0.0022	0.0007	0.0024	0.0016
	0.08	0.08	0.05	[1.19]	[0.42]	[0.30]
PercentReturn11	0	0.0011	0.0043	0.001	0.0043	0.0033
	0.09	0.08	0.05	[1.68]	[0.74]	[0.58]
PercentReturn12	-0.0001	0.0012	0.0048	0.0013*	0.0049	0.0036
	0.09	0.09	0.06	[1.97]	[0.80]	[0.58]
PercentReturn13	-0.0002	0.0012	0.0067	0.0014*	0.0069	0.0055
	0.09	0.09	0.06	[2.07]	[1.07]	[0.86]
PercentReturn14	-0.0003	0.0008	0.0056	0.0011	0.0059	0.0048
	0.1	0.09	0.07	[1.58]	[0.91]	[0.79]
PercentReturn15	-0.0002	0.0003	0.006	0.0006	0.0063	0.0057
	0.1	0.09	0.07	[0.80]	[0.96]	[0.92]
PercentReturn16	-0.0002	0.0003	0.0051	0.0005	0.0054	0.0048
	0.1	0.09	0.07	[0.72]	[0.79]	[0.77]
PercentReturn17	-0.0003	0.0005	0.0053	0.0007	0.0055	0.0048
	0.1	0.1	0.08	[0.95]	[0.79]	[0.68]
PercentReturn18	-0.0003	0.0006	0.0076	0.0009	0.0079	0.0071
	0.11	0.11	0.08	[1.15]	[1.10]	[0.94]
PercentReturn19	-0.0001	0.0004	0.0083	0.0004	0.0083	0.0079
	0.11	0.11	0.08	[0.57]	[1.13]	[1.08]
PercentReturn20	0.0001	0.0001	0.0102	0	0.01	0.0101
	0.11	0.11	0.08	[-0.02]	[1.32]	[1.40]
PercentReturn21	0.0003	0.0002	0.0143	-0.0001	0.014	0.0141
	0.12	0.11	0.09	[-0.09]	[1.78]	[1.87]
PercentReturn22	0.0003	0.0005	0.0136	0.0002	0.0133	0.0131
	0.12	0.12	0.1	[0.19]	[1.64]	[1.67]
PercentReturn23	0.0001	0.0003	0.014	0.0003	0.0139	0.0137
	0.12	0.12	0.09	[0.29]	[1.69]	[1.71]
PercentReturn24	-0.0003	-0.0001	0.0098	0.0001	0.0101	0.0099
	0.12	0.12	0.1	[0.16]	[1.19]	[1.22]
PercentReturn25	-0.0004	-0.0004	0.0121	0	0.0125	0.0125
	0.13	0.12	0.1	[-0.00]	[1.46]	[1.51]
PercentReturn26	-0.0002	-0.0004	0.0151	-0.0003	0.0153	0.0155

	0.13	0.12	0.1	[-0.28]	[1.74]	[1.85]
PercentReturn27	-0.0002	-0.0005	0.0127	-0.0004	0.0128	0.0132
	0.13	0.13	0.1	[-0.38]	[1.43]	[1.54]
PercentReturn28	-0.0001	-0.0005	0.0103	-0.0004	0.0104	0.0108
	0.14	0.13	0.1	[-0.38]	[1.12]	[1.22]
PercentReturn29	0.0003	0	0.0103	-0.0004	0.01	0.0103
	0.14	0.13	0.1	[-0.35]	[1.05]	[1.15]
PercentReturn30	0.0006	0.0003	0.0135	-0.0003	0.0129	0.0132
	0.14	0.13	0.1	[-0.30]	[1.33]	[1.45]
Observations	1879262	19283	218	1898545	1879480	19501

Appendix 27: abnormal returns conditional on 30d = 1

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider	in listed	insider	dif 1,2	dif 1,3	dif 2,3
	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t	mean/b/sd/t
PercentReturn1	-0.0001	0.0001	0.0027	0.0002	0.0028**	0.0026**
	0.03	0.02	0.03	[1.73]	[2.72]	[2.74]
PercentReturn2	-0.0002	0.0001	0.0031	0.0003*	0.0033*	0.0030*
	0.04	0.03	0.03	[2.11]	[2.37]	[2.34]
PercentReturn3	-0.0004	-0.0001	0.0028	0.0004*	0.0033*	0.0029*
	0.04	0.04	0.04	[2.05]	[2.04]	[2.08]
PercentReturn4	-0.0006	-0.0003	0.0031	0.0003	0.0037*	0.0034*
	0.05	0.04	0.04	[1.65]	[2.02]	[2.08]
PercentReturn5	-0.0008	-0.0005	0.0029	0.0003	0.0037	0.0034
	0.05	0.05	0.04	[1.36]	[1.82]	[1.95]
PercentReturn6	-0.0007	-0.0005	0.0035	0.0003	0.0042	0.0040*
	0.06	0.05	0.05	[1.11]	[1.92]	[2.11]
PercentReturn7	-0.0008	-0.0004	0.0044	0.0004	0.0052*	0.0048*
	0.06	0.05	0.05	[1.36]	[2.20]	[2.38]
PercentReturn8	-0.0007	-0.0003	0.0029	0.0004	0.0036	0.0032
	0.06	0.06	0.05	[1.59]	[1.48]	[1.49]
PercentReturn9	-0.0008	-0.0002	0.0028	0.0006*	0.0037	0.0031
	0.07	0.06	0.05	[2.05]	[1.42]	[1.34]
PercentReturn10	-0.0008	-0.0002	0.0035	0.0006*	0.0043	0.0037
	0.07	0.06	0.05	[2.00]	[1.61]	[1.55]
PercentReturn11	-0.001	-0.0004	0.0029	0.0006	0.0038	0.0033
	0.07	0.07	0.06	[1.78]	[1.36]	[1.26]

PercentReturn12	-0.0008	-0.0003	0.0024	0.0005	0.0032	0.0027
	0.08	0.07	0.07	[1.41]	[1.09]	[1.01]
PercentReturn13	-0.0007	-0.0001	0.0029	0.0005	0.0036	0.0031
	0.08	0.07	0.07	[1.60]	[1.19]	[1.09]
PercentReturn14	-0.0007	-0.0002	0.0039	0.0005	0.0046	0.0041
	0.08	0.07	0.07	[1.38]	[1.48]	[1.44]
PercentReturn15	-0.0008	-0.0004	0.0041	0.0004	0.0048	0.0044
	0.08	0.08	0.07	[1.13]	[1.51]	[1.50]
PercentReturn16	-0.001	-0.0005	0.0039	0.0005	0.0049	0.0044
	0.09	0.08	0.07	[1.28]	[1.48]	[1.43]
PercentReturn17	-0.0011	-0.0006	0.0034	0.0005	0.0045	0.0041
	0.09	0.08	0.08	[1.20]	[1.33]	[1.28]
PercentReturn18	-0.0012	-0.0007	0.0029	0.0004	0.0041	0.0037
	0.09	0.09	0.08	[1.09]	[1.17]	[1.13]
PercentReturn19	-0.0012	-0.0009	0.0033	0.0003	0.0045	0.0041
	0.09	0.09	0.09	[0.83]	[1.25]	[1.18]
PercentReturn20	-0.0013	-0.001	0.0049	0.0003	0.0062	0.0059
	0.1	0.1	0.09	[0.82]	[1.69]	[1.59]
PercentReturn21	-0.0013	-0.001	0.0044	0.0003	0.0057	0.0054
	0.1	0.1	0.09	[0.74]	[1.53]	[1.49]
PercentReturn22	-0.0014	-0.0008	0.0034	0.0006	0.0048	0.0042
	0.1	0.1	0.09	[1.29]	[1.24]	[1.15]
PercentReturn23	-0.0014	-0.0008	0.0038	0.0006	0.0052	0.0046
	0.1	0.1	0.1	[1.34]	[1.33]	[1.23]
PercentReturn24	-0.0013	-0.0007	0.0029	0.0005	0.0041	0.0036
	0.1	0.1	0.1	[1.21]	[1.04]	[0.93]
PercentReturn25	-0.0013	-0.0008	0.0029	0.0005	0.0042	0.0037
	0.11	0.1	0.1	[1.12]	[1.03]	[0.94]
PercentReturn26	-0.0011	-0.0006	0.0043	0.0005	0.0054	0.0049
	0.11	0.1	0.1	[1.06]	[1.31]	[1.24]
PercentReturn27	-0.001	-0.0004	0.0034	0.0006	0.0044	0.0038
	0.11	0.1	0.1	[1.21]	[1.05]	[0.96]
PercentReturn28	-0.001	-0.0005	0.0027	0.0004	0.0037	0.0032
	0.11	0.11	0.1	[0.91]	[0.86]	[0.79]
PercentReturn29	-0.0009	-0.0003	0.0027	0.0006	0.0036	0.003
	0.11	0.11	0.1	[1.14]	[0.83]	[0.74]
PercentReturn30	-0.0009	-0.0005	0.0027	0.0004	0.0036	0.0032
	0.11	0.11	0.1	[0.90]	[0.83]	[0.77]
Observations	5662072	54689	691	5716761	5662763	55380

Appendix 28: abnormal returns conditional on 30d = 0

	(1)	(2)	(3)	(4)	(5)	(6)
	outsider mean/b/sd/t	in listed mean/b/sd/t	insider mean/b/sd/t	dif 1,2 mean/b/sd/t	dif 1,3 mean/b/sd/t	dif 2,3 mean/b/sd/t
PercentReturn1	-0.0002	0.0002	-0.0018	0.0004	-0.0016	-0.002
	0.03	0.03	0.02	[1.54]	[-0.73]	[-1.03]
PercentReturn2	-0.0002	0.0004	-0.0025	0.0006	-0.0023	-0.0029
	0.04	0.04	0.03	[1.89]	[-0.79]	[-1.11]
PercentReturn3	-0.0002	0.0005	-0.0021	0.0007*	-0.0018	-0.0026
	0.05	0.05	0.03	[2.10]	[-0.55]	[-0.71]
PercentReturn4	-0.0001	0.0003	-0.0034	0.0004	-0.0033	-0.0038
	0.05	0.06	0.03	[1.12]	[-0.89]	[-0.95]
PercentReturn5	-0.0002	0.0003	-0.0016	0.0005	-0.0015	-0.002
	0.06	0.05	0.03	[1.19]	[-0.37]	[-0.54]
PercentReturn6	-0.0004	0.0001	0.0003	0.0005	0.0006	0.0002
	0.06	0.06	0.03	[1.01]	[0.15]	[0.04]
PercentReturn7	-0.0005	-0.0003	-0.0016	0.0002	-0.0011	-0.0013
	0.07	0.07	0.04	[0.39]	[-0.24]	[-0.28]
PercentReturn8	-0.0004	-0.0001	0.0015	0.0003	0.0018	0.0016
	0.07	0.07	0.04	[0.49]	[0.38]	[0.32]
PercentReturn9	-0.0005	-0.0003	0.0009	0.0002	0.0013	0.0011
	0.07	0.07	0.04	[0.41]	[0.26]	[0.22]
PercentReturn10	-0.0006	-0.0003	-0.0017	0.0003	-0.0011	-0.0014
	0.08	0.07	0.04	[0.50]	[-0.21]	[-0.27]
PercentReturn11	-0.0003	0.0003	-0.0008	0.0007	-0.0005	-0.0011
	0.08	0.08	0.04	[1.14]	[-0.09]	[-0.21]
PercentReturn12	-0.0004	0.0005	-0.0008	0.001	-0.0004	-0.0013
	0.08	0.09	0.05	[1.59]	[-0.06]	[-0.22]
PercentReturn13	-0.0004	0.0007	0.0014	0.0011	0.0019	0.0007
	0.09	0.09	0.05	[1.78]	[0.31]	[0.12]
PercentReturn14	-0.0005	0.0004	-0.0002	0.0009	0.0003	-0.0006
	0.09	0.08	0.06	[1.40]	[0.05]	[-0.11]
PercentReturn15	-0.0005	0	-0.0003	0.0005	0.0002	-0.0003
	0.09	0.08	0.06	[0.74]	[0.03]	[-0.05]
PercentReturn16	-0.0005	-0.0001	-0.0009	0.0004	-0.0004	-0.0008
	0.09	0.09	0.06	[0.58]	[-0.06]	[-0.13]
PercentReturn17	-0.0006	0	-0.0003	0.0006	0.0003	-0.0003
	0.1	0.1	0.07	[0.87]	[0.04]	[-0.05]
PercentReturn18	-0.0006	0.0003	0.0023	0.0009	0.0029	0.002
	0.1	0.1	0.07	[1.17]	[0.42]	[0.29]

PercentReturn19	-0.0005	0.0001	0.002	0.0006	0.0025	0.0019
	0.1	0.1	0.07	[0.78]	[0.35]	[0.27]
PercentReturn20	-0.0003	-0.0001	0.003	0.0002	0.0033	0.0031
	0.1	0.1	0.07	[0.25]	[0.47]	[0.47]
PercentReturn21	-0.0002	-0.0001	0.0067	0.0001	0.0069	0.0068
	0.11	0.1	0.08	[0.13]	[0.94]	[0.98]
PercentReturn22	-0.0001	0.0001	0.0058	0.0002	0.0058	0.0057
	0.11	0.1	0.09	[0.24]	[0.78]	[0.78]
PercentReturn23	-0.0004	-0.0002	0.0049	0.0002	0.0053	0.0051
	0.11	0.11	0.08	[0.24]	[0.69]	[0.69]
PercentReturn24	-0.0006	-0.0005	0.0008	0.0001	0.0014	0.0014
	0.11	0.11	0.09	[0.07]	[0.18]	[0.18]
PercentReturn25	-0.0007	-0.0009	0.0033	-0.0002	0.004	0.0042
	0.12	0.11	0.09	[-0.21]	[0.49]	[0.54]
PercentReturn26	-0.0007	-0.0011	0.0064	-0.0004	0.0071	0.0075
	0.12	0.11	0.09	[-0.47]	[0.86]	[0.96]
PercentReturn27	-0.0009	-0.0011	0.0038	-0.0003	0.0046	0.0049
	0.12	0.12	0.09	[-0.31]	[0.55]	[0.61]
PercentReturn28	-0.0009	-0.0012	0.002	-0.0003	0.003	0.0033
	0.13	0.12	0.09	[-0.31]	[0.34]	[0.40]
PercentReturn29	-0.0008	-0.0012	0.0032	-0.0004	0.004	0.0044
	0.13	0.12	0.09	[-0.40]	[0.45]	[0.53]
PercentReturn30	-0.0007	-0.001	0.0052	-0.0003	0.0059	0.0062
	0.13	0.12	0.09	[-0.32]	[0.65]	[0.74]
Observations	1837644	18925	210	1856569	1837854	19135