PROFITING FROM UNCERTAINTY

A STUDY ON THE INFORMATIVENESS OF INSIDER TRADES DURING THE COVID-19 PANDEMIC

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Bachelor Thesis

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Profiting from uncertainty: A study on the informativeness of insider trades during the COVID-19 pandemic.

Abstract

Using publicly available data on insider trades made in constituent companies of the S&P 500, this paper examines the return of- and market reactions to insider trades made during the first six months of the COVID-19 pandemic. Our results show that insider trading activity peaked in the early months of the pandemic, that insiders did possess predictive ability concerning future stock development and that they hence were able to beat the market during our sample period. We conclude that there was no identifiable correlation between insider trading activity and insider returns earned in specific industries. Moreover, the sample data shows that the market priced large stocks more efficiently than small stocks during the COVID-19 outbreak. We find that insider traders were successful in predicting long-term stock price increases and decreases during the COVID-19 pandemic, and that insider trades hence were informative as signals to buy or sell a stock. We also conclude that the stock market largely ignored the signals given by insiders or just did not price it efficiently, which suggests that the market did not trust insider trades as signals during the pandemic although they should have. We do not reach significant results for our difference-in-difference regression which caps our capability of comparing insider trading during the pandemic to insider trading in non-pandemic times.

Keywords

COVID-19, Insider Trading, NPR, SEC, Market Reactions.

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1. Introduction

1.1 Background

Towards the end of 2019, the contagious and deadly SARS-CoV-2 virus began spreading from the city of Wuhan in China, and had by the beginning of March 2020 reached 114 countries worldwide (WHO, 2020). The virus later became more known as COVID-19 and has as of 2022 reaped more than 6,100,000 lives worldwide (Statista, 2022). As a consequence of the rapidly spreading virus, many countries imposed restrictions throughout the spring of 2020, ranging from light recommendations to month-long lockdowns in order to limit the spread of the virus. As borders closed, international trade was severely impaired and the general uncertainty was high, stock markets started plunging. In what afterwards was named the Coronavirus Crash of 2020, the US stock markets experienced the three worst market drops in points in US history (Forbes, 2021). Generally, economic unpredictability of this kind leads to stock market volatility at some point (Ahmad and Ramzan, 2016). Negative news cause the stock market to drop and the drop is further accelerated by an overreaction causing panic selling by both investors and automatically triggered algorithms. The behavioral nature of the reactions raises an interesting question: Would a better-informed investor be able to make a financially more sound decision in times of great uncertainty? Can outside traders benefit by following the trades made by an insider?

A security trade is labeled to be an "insider trade" if the trader is someone with great insight into the company such as a C-level executive, a shareholder of 10% or more, a board member, director, manager or similar. There are extensive law chapters that have been passed in order to control insider trading, which in practice means that insiders have to report all the trades they make to the Securities and Exchange Commission (the SEC) in the U.S. These filings become public information as soon as they have been sent by the insider, which enables everyone to screen them. Insider trades have a certain signaling value, showing the market how the insiders value their firms. As a consequence they are actively followed by both business magazines and individuals. The base assumption is that insiders have greater knowledge and insight than external investors, causing them to be more informed and their purchase (sell) transactions to be an indication of future increases (decreases) in the price of the security. Whether these signals are valuable or not depends on the actual informativeness of the trades and is a repeatedly debated subject. This thesis aims to further contribute to the discussion by addressing insiders' informativeness during periods of crisis.

Between the start of February and the end of March 2020, insiders of US-traded companies sold shares for roughly $9.2 billion in their own companies (The Wall Street Journal, 2020). Previous research has shown that insiders are better informed than the market and indeed earn abnormal returns (Seyhun, 1986). However, that research did not dive deeper into the implications of insider trading in times of crisis, when the market is more desperate for information than ever as it seeks indications of how companies will perform in the new conditions forced upon them by the crisis. Seyhun (1988, 1992, 1998) showed that insider traders seem to predict future market movements and that they are contrarian investors. Fama and French (1988) argue that it is possible that insiders can predict market movements simply because they are contrarian. Whether this was true or not under the pandemic is something we try to address.

The COVID-19 pandemic in general, and insider trading during the spring of 2020 in specific, compose an interesting area of economic research as it is a current event whose effects still haven't been thoroughly documented by existing academia. Moreover, it would be interesting to investigate how insiders acted under the most global crisis, whether they engaged more or less in trading and whether there were any detectable reasons that either kept insiders away from trading on their knowledge during the crisis or not.

1.2 Research Questions

The recency of the subject of this thesis and the potential use of understanding insider trading during times of crisis for future use for both investors and researchers have prompted us to try to answer questions that would help the above-mentioned actors in navigating the topic. This paper studies the stock returns of the 494 largest public companies in the US during the first six months of 2020, the period covering the Coronavirus Crash of 2020, in order to try to answer the the following research questions:

i. How did the market react to insider trading during the advent of the COVID19 pandemic?

ii. Were insiders able to predict future stock development and earn abnormal profits on their trades made during the pandemic?

iii. Were there any detectable patterns in insider trading during the pandemic?

1.3 Methodology

The thesis is to large extent an extension on Lakonishok and Lee's (2001) paper "Are Insider Trades Informative?". The authors showed that insider trading often is financially beneficial to the insider, but ignored by the market. We extend on Lakonishok & Lee's findings by applying a similar methodology in a new setting, namely during the first six months of the Covid-19 pandemic. The purpose is to measure the signaling value of insider trades in times of great economic uncertainty as well as to evaluate the informativeness of the trades. We first present summary statistics over insider sales and purchases during the first six months of the pandemic, reported for small, medium and large firms where the groups have been created on market cap basis. Like the above-mentioned authors, we measure short-term market reactions to insider trades by considering the abnormal return of the securities during the days surrounding each trade. Abnormal return is calculated by subtracting the equally weighted S&P 500 return from the individual stock return of a five-day period. The S&P 500 is thus used as a proxy for overall market return.

Following the methodology of Lakonishok & Lee, we also evaluate the performance of the securities over longer time periods to determine the informativeness of the trades performed during the spring of 2020, and their ability to predict stock returns. To determine whether aggregate insider activity during the pandemic was able to predict stock development, we calculate a Net Purchase Ratio (NPR) for all sample companies based on their insider activity during January to June 2020. The NPR is calculated by dividing the net aggregate number of insider purchases by the total aggregate number of insider transactions over the given six-month period. The net number of insider purchases is calculated by subtracting the total amount of insider sales from the total number of insider purchases. We further divide the securities into 10 portfolios, based on their NPR as of the formation date, 2020-07-30. The portfolios are created using the company's decile belongings, based on NPR. The lowest decile constitutes portfolio 1 and the highest decile portfolio 10.

Informed traders should make profitable transactions, implying that stocks with extensive insider purchasing (selling) should show positive (negative) return looking forward, as the price of the stocks increases (decreases), as predicted. The informativeness of the insider trading activity is thereby evaluated by looking at the performance of the NPR portfolios following the formation date. In other words, by evaluating if companies with extensive insider purchasing (selling), i.e. high (low) NPR, during the start of the Codvid-19 pandemic, showed increasing (decreasing) stock prices following the six month period. This is done by looking at both raw and abnormal returns for different time intervals, from 6 months after the formation date and up until now, february 2020.

We attempt to distinguish between returns produced by insider trading and returns based on simple contrarian strategies by looking at post stock performance and synthesizing it in a table with post-trade stock return.

We further divide our data into three size groups depending on the securities market capitalization, and calculate the average NPR for these three size groups. Despite Lakonishok & Lee calculating NPR's on insider transactions undertaken by managers, large shareholders and a combination of both, we have refrained from doing so as our data sources did not allow us to include that data in a way that did not incur extensive manual labor. What further motivated this exclusion was the non-significant findings of Lakonishok & Lee for the individual groups mentioned. We group our sample firms into three B/M (book-to-market) equity groups and three size groups based on market capitalization. With the respective groups, we define the bottom three deciles as "Low B/M" and "Small Firms", the middle four deciles as "Medium B/M" and "Medium Firms", and the top three deciles as "High B/M" and "Large Firms". We further calculate the average NPR of each group. The goal is to be able to distinguish patterns between stocks with similar characteristics.

Moreover, we divide our data on industry-basis to control for industry-related outlying results that may have been abnormally impacted by the pandemic in any direction and hence weighting our total results in a misleading direction. We also try to distinguish certain trends within different industries. The industries used are the GICS sector classifications. Our results are reported in Table 6, and we have created NPR portfolios within each industry and calculated the average NPR for each industry.

Lastly we run regressions on raw return, abnormal return and a difference-in-differences regression. We run separate regressions for raw return and abnormal return as we want to control for potential coefficient differences between what beats the market and what does not. We run separate regressions on both raw returns and abnormal returns with and without dummies that control for strong buy- and sell signals, which are given by an NPR>0.7 (strong buy signal) or <-0.7 (strong sell signal), and another regression where we include dummies that control for industry fixed effects. Companies with negative B/M are excluded in the regressions we make. Variables such as the logarithm of market capitalization, the logarithm of book-to-market value, post 24 months return and post 12 months return are included as control variables, controlling effects of different characteristics as well as possible contrarian strategies.

In our DiD analysis we compare our data from 2020 with comparable data from 2018. The reason behind choosing 2018 and not 2019 is that since we compare return data on a one-year basis after insider trades, data from 2019 would include returns that would have been impacted by the pandemic which entered the scene in the winter 2019/2020, which would nullify our comparison. The dummies included in our DiD analysis are one for NPR and one for year, as well as a DiD-dummy.

1.4 Results

Our results show that insiders were active in the beginning of the pandemic, seeing a peak in insider trading in general and insider sales in specific in the early months of 2020. Moreover, our data shows that stocks bought by insiders to a high degree deliver great return in the long-term, which suggests that aggregate insider trading seems to have been predictive of future market movements, and could be used as a tool to time the market, which is in-line with previous studies by Seyhun (1988, 1998) and Lakonishok and Lee (2001). Additionally, we find that insiders who sold off stock also were predictive of future negative stock development, which diverts from findings in previous literature, which has concluded that insider sales are not predictive of stock price downturns. In our data, this is shown by the low NPR portfolios, who thus have a relatively big proportion of insider sellers, generated negative return post-insider trade. Our finding is indicated by the highest NPR portfolio earning 14,65% higher return than the lowest NPR portfolio in twenty months time, which is our longest measured period. Moreover, we do find that large companies were priced more efficiently than smaller companies during the COVID-19 pandemic, shown by lower abnormal return in larger companies, hinting about insider information already being included in the pricing of the stock, which is consistent with previous research (Lakonishok & Lee, 2001) made on stock pricing in non-crises. In line with the findings of Lakonishok and Lee, we find that the biggest potential benefit in exploiting insider trading activity lied in smaller companies during the COVID-19 pandemic. We find that insiders in smaller companies are successful in predicting stock price increases, more so than insiders in larger companies. In the regressions we run we get significant results when including dummies that indicate strong buy or sell signals. The regressions suggest that a strong buy signal is associated with a 0.096 increase in return, while a strong sell signal is associated with a -0.115 decrease in return. Moreover, we get that there is a negative correlation between NPR and return of -0.097. We do not find any pattern related to industries and impact of the COVID-19 pandemic regarding NPR or returns. We do not achieve significant results for the difference-in-differences regression that we run between 2020 and 2018 beyond for one dummy, which hence limits the conclusions we can draw from how insider trading during the pandemic differed from the trend line of insider trading. The year-dummy suggests that there were higher returns in 2020 compared to in 2018 but beyond that we cannot conclude anything of substance.

2. Theoretical framework and Literature review

As previously mentioned, the paper that has inspired the production of this thesis is "Are Insider Trades Informative?" by Lakonishok and Lee (2001). In the article the authors investigate insider trading over a 20-year period, from 1975 to 1995, with the goal of mapping how insider trading has developed over time as well as to see if insiders earn abnormal returns and whether the insider trades have any substantial effects on the market, in the form of market reactions following the insider trade.

We have used the same methodology as the above-mentioned researchers, but our thesis differs from their article in a few essential ways. One concerns the time period and the generality of the conclusions. Lakonishok and Lee endeavor to analyze insider trading over a long period of time, hence researching insider trading behavior and consequences under "normal conditions", and are thus able to draw generalizing conclusions about insiders ability to predict market movement and earn abnormal returns, in general. We are interested in investigating insider trading under extreme conditions, more specifically during the dawn of the COVID-19 pandemic that started in 2020. This paper seeks to draw conclusions related to insider trading during the first hectic six months of 2020, wherein the worst financial turmoil known as the Coronavirus Crash of 2020 went down, while our predecessors sought conclusions on a general level without diving deep into any specific set of conditions. With that being said, the potential contribution of our thesis to the existing literature on this topic is revealing potential differences in insider trading behavior, profits and market reactions to those insider trades under circumstances of extreme uncertainty. Learnings from this paper could thus be used to understand the value of insider signals given by their trading in times when valuing stocks is a close-to-impossible task, considering that great uncertainty about the future and the company's place in it often are accompanies crises like the one we experienced throughout the last two years. Another aspect of what both Lakonishok and Lee as well as Seyhun brings up in their studies that we check for as well, is contrarian strategies, meaning insiders tend to buy stocks when they have performed badly. We must then check whether insiders simply use contrarian strategies or if they time the market and buy undervalued stock due superior information possession.

Moreover, we do reference different forms of the efficient market hypothesis in our thesis, which is a concept first mentioned by Fama (1970). There are three forms of the effective market hypothesis. The strong version claims that in an effective market there are no barriers to the flow of information, all information is accounted for in the stock price and there exist no information asymmetries. In such a market, no investor can make a more informed investment decision than his or her peers. In other words, even insiders should not be able to make more informed decisions and should therefore not be able to earn abnormal profits, i.e. beat the market. The semi-strong form submits that no technical or fundamental analysis will help an investor gain advantage over the market. The only way of doing so is using non-public information. The weak form of the effective market hypothesis suggests that the stock price accounts for the data of past stock prices, rendering technical analysis useless but fundamental analysis useful for an investor in determining whether a stock is over- or undervalued. The methodology we use in this thesis, where we measure raw and abnormal returns earned by insiders during the COVID-19 pandemic and compare them to returns made in 2018 in a differences-in-difference analysis, does thus have implications for our perception of an efficient market. Does a pandemic make the market more or less efficient? In other words, does the uncertainty brought about by a pandemic or crisis impact which form of the efficient market hypothesis that is relevant to take into consideration, and what implications does that in that case have in terms of market reactions to insider trades? Does the potential information advantage held by insiders increase in a pandemic when general uncertainty is widespread? After Fama, there have been studies that show that we do not have a completely efficient market and that there are delays in the incorporation of news into stock prices [Busse and Green (2002), Patell and Wolfson (1984), Jennings and Starks (1985), Barclay and Litzenberger (1988)]. Comparing the studies of Lloyd Davied and Canes (1978) and Busse and Green (2002), it becomes evident that markets have become more efficient over the years: while the former found that stock prices adjusted for news in a matter of minutes, the latter found that stock prices adjusted for news in a matter of seconds.

In this thesis, the efficient market hypothesis is of interest as we want to measure whether the market considers insider signaling and prices it into the stock price during a time when uncertainty is ubiquitous. If it would, we would expect stock prices of stocks that insiders have bought to be pushed upwards in the short-term, and the reverse for insider sales. By checking for this, we can test the market's efficiency during a crisis, using the base assumption of the semi-strong form of the EMH suggesting that insiders do know more than external investors.

Marin (2013) found that insider purchases peak before a big increase in the stock price, and that insider sales tend to be as most intensive right before a financial crash, such as the one the markets experienced in the spring of 2020. This paper tests the findings by Marin in a new setting to check if the conclusions of the paper holds also for a financial crash caused not by the default of financial instruments or illiquidity in the market, but by a deadly pandemic that decimates the worldwide labor force and hence has graver potential consequences for the economic activity in the world long-term. Moreover, a pandemic comes suddenly and with no direct link to financial fundamentals, which means that smart economists will not have the same prerequisites to predict a crash induced by a pandemic compared to a financial bubble. We do however not use the methodology used by Marin, but are able to put his findings under new light with the purpose of drawing conclusions about the insider's predictive ability of their own stocks. Additionally, Marin concluded that insiders tend to reach the peak of selling several months prior to the drop of the stock price. The reason behind this is hypothesized in the article to be because of insiders being prohibited to trade on non-public information, and in order to avoid SEC scrutiny they execute their trading orders many months ahead of an announcement that will impact the stock price. We compare insider's behavior in this regard under new circumstances, namely the COVID-19 pandemic.

There is already plenty of research published on the matter of insider trading that has concluded that insiders do in fact earn abnormal returns [Seyhun (1986, 1998), Eckbo and Smith (1998), Jeng, Metrick and Zeckhauser (1999)]. The aim of this study is to investigate whether this held true during the COVID-19 pandemic, when forecasting and hence valuing stocks were harder than in a long time.

3. Data

Our sample consists of data from 494 constituent firms taken of the S&P 500 index as of February 2022. We decided to use the S&P 500 constituents as our sample because of the following reasons:

1. The S&P 500 includes companies from a wide array of industries, hence eliminating the risk of industry-specific noise in our data.
2. The index provides us with a quantity of companies substantial enough to analyze and draw generalizing conclusions from.
3. It covers the dominant companies in the US, accounting for over 75% of the total market capitalization of US companies across all exchanges.

Some data was retrieved from CRSP and Compustat via the WRDS database during the spring of 2022, when this study was conducted. This includes the data over closing day stock prices needed to calculate returns, the data over current market capitalization of our sample firms as well as these companies' respective B/M ratios. When this study was written, the S&P 500 consisted of a total of 505 securities. The discrepancy between the 505 securities in the index and the 494 stocks we have included in our data set has its explanation. The WRDS database lacked data on stock price for 11 of the securities in the index for the period 2018-2022, which was crucial data for a stock to be included in this study. One natural explanation for this is that some firms have more than one security, with different voting rights, etc. Of the 494 stocks included 479 companies had any insider trading happening under our sample period.

Data over the insider transaction was obtained from WRDS and the section *Insiders Data by WRDS*. It covers all non-derivative insider transactions performed and reported, in the sample companies during the spring of 2020. The dataset is based on the reports sent in by the companies to the Securities and Exchange Commission's (the SEC), which contains all insider transactions that are subject to disclosure according to Section 16(a) of the Securities and Exchange Act of 1934. The data used in this study is from Form 4-filings, which is a filing that must be sent to the SEC whenever there is any change in beneficial ownership of a company made by an insider.

Unlike Lakonishok & Lee (2001), we choose to not classify our data into different groups depending on the type of insider, i.e. "Management", "Large Shareholders" and "Others". There are two reasons behind this exclusion. The first one is that we faced issues with finding and synthesizing data on type of insider with our other data. The other is that the vast majority of insider traders are in the company management. Previous research has found that only a small fraction of the insider trades are performed by large shareholders (Lakonishok & Lee, 2001). This means that the results we would receive if we were to include that division in our thesis would either way be heavily weighted towards the results of insiders pertaining to the management group. We then deduced that we could proceed with our study without including the type of insider without losing important nuance or substance to this thesis.

One reminder that Lakonishok & Lee included in their paper and that may be of use to mention here as well is that commercial banks, investment banks, insurance companies, investment advisers, pension funds, brokers, employee benefit plans and mutual funds do not need to report their trading of a certain stock even if they hold more than 10% of the shares in the company as long as they acquired the shares without the intention to change or influence control over the company. Many institutional investors do however report their transactions as a precaution to possible legal action against them. This means that there may be some major trades that are not included in our sample due to them being executed by any above-mentioned entity which would have exercised their right to not report the trade to the SEC.

In this study we look at two types of trading: "Sales" and "Purchases", which refer to open-market or private purchases and sales of stock. These are derived from the Form 4-filings from the SEC, which are the forms that report insider sales and purchases. Sales of shares acquired by exertion of options are categorized as "Sales". Other transactions and types of securities are excluded from this study. While Lakonishok & Lee presented a third trading type, "Option", we have excluded this category. The "Option" category referred to the acquisition of shares through exercising options, warrants or convertible bonds. The reason we exclude this category from our study is that our working hypothesis is that the market signal of an insider exercising an option to acquire a share will be far more ubiquitous compared to the non-option acquisition of the stock by the insider. As US federal law requires public companies to disclose the compensation of high-ranking officers, any investor interested in options that may be exercised by a C-level employee of the company can be found in the latest 10-K filed by the company on the EDGAR portal. With that being said, exercising options should be included in the current pricing of the stock and hence it is excluded from our thesis.

The data on sales and purchases is then used to calculate NPR for each company and group, whose calculation is given by:

$$NPR = \frac{Net\ Aggregate\ Number\ of\ Insider\ Purchases}{Total\ Aggregate\ Number\ of\ Insider\ Transactions}$$

Throughout the following article we categorize our sample firms into three size and three book-to-market (B/M) equity groups. B/M is calculated by the following equation:

$$B/M = \frac{Book\ Equity\ Value}{Market\ Value\ of\ Equity}$$

We also look at the abnormal return of different stocks and groups, calculated as:

$$Abnormal\ Return = Return - Equally\ weighted\ return\ of\ the\ group/sample/quintile$$

4. Summary Statistics

Table 1 presents summary statistics for each category of sirm size and transaction type, for the treatment period of January - June 2020. Presented are the average number of trades per firm during the period and the average fraction of companies with at least one insider transaction of respective type; purchase or sale. Statistics are also shown for the total sample and both transactions together. Table 2 presents the monthly statistics over our sample firms' insider trading activity over the period January-June 2020. Both the number of trades made during the period as well as the fraction of firms in our sample with at least one insider purchase or sale is given by Table 2.

Our first (1) hypothesis was that insider trading would be more frequent in larger companies compared to small companies, as a result of larger companies having greater headcount than smaller ones and hence having more insiders that can trade. Moreover, as larger companies are more heavily scrutinized we expect more trading activity in these companies. Additionally, (2) we expected insiders to have sold more in the very start of the pandemic but have started to purchase more after the big index drops that happened in the Corona Crash, due to panic selling and a better understanding than the market of when their own stock is undervalued. Lastly, (3) we suspect a peak in the number of insider trades around the Corona Crash of 2020, caused by panic selling and a domino effect of it, as well as contrarian strategies are expected to kick in.

The results showed in Table 1 that there was at least one insider trade in 91% of our sample firms in 2020, and that a typical company during our sample period averages 26,51 insider trades during our sample period of six months (14,24 purchases and 12,27 sales). In the article written by Lakonishok & Lee (2001), their sample of companies and insider trades in those companies between 1975-1995 averaged 20 trades a year, with sales exceeding purchases by far. This means that we saw more insider trades during six months than Lakonishok & Lee denoted per year. Hence, our results show that insider trading has increased significantly since the 1990's. It is reasonable to assume however that this level of insider trading is abnormal and caused by the circumstances of the pandemic, even if it would have increased incrementally over the years since Lakonishok and Lee conducted their study.

Table 1: Summary Satistics

	Both transactions	Purchases	Sales
Total (494 firms)			
Fraction	0,91	0,95	0,93
# of Trades	26,51	14,24	12,27
Small firms (148 firms)			
Fraction	0,86	0,93	0,91
# of Trades	25,66	14,37	11,29
Medium firms (198 firms)			
Fraction	0,92	0,96	0,93
# of Trades	25,26	13,83	11,43
Large firms (148 fiirms)			
Fraction	0,95	0,97	0,96
# of Trades	29,03	14,67	14,36

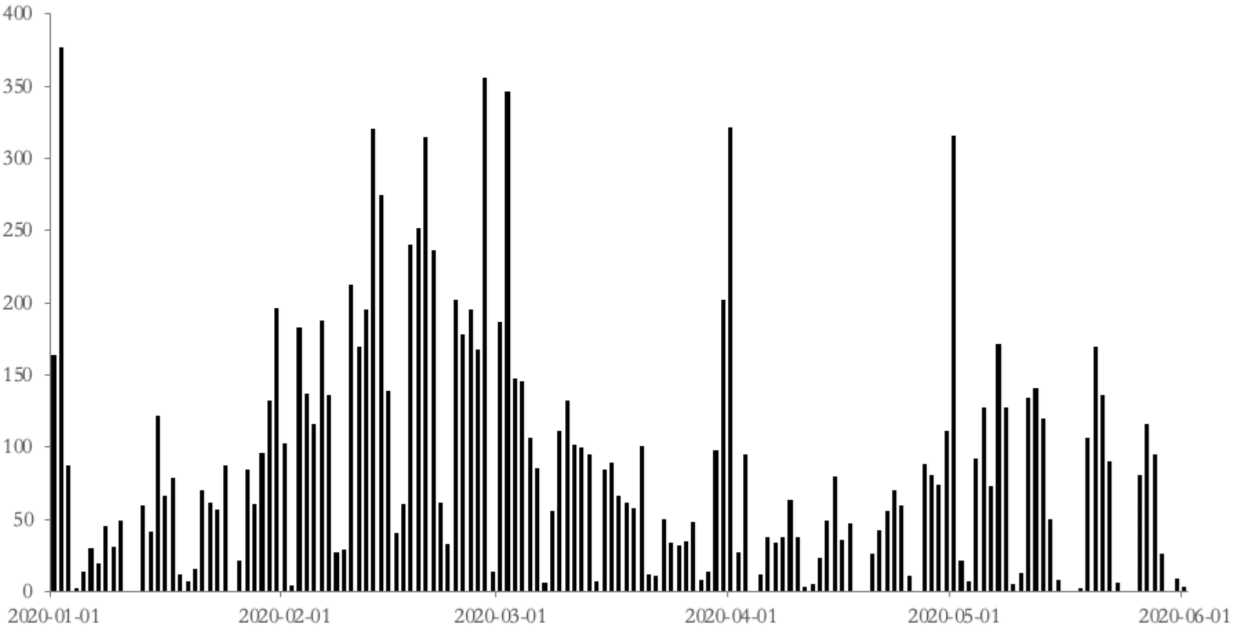
The table reports summary statistics of insider trading for all S&P 500 firms during january to june 2020. Excleded from the sample are shares that doesn't appear in CRSP/Compustat merged "Security Daily" dataset for the period. "Purchases" includes all types of aquiering of shares. "Sales" includes all types of disposal of shares. "Fraction" represents the fraction of firms with at least one trade of each type. "# of trades" refers to the average number of trades per company for the 6 month period. "Small", "Medium" and "Large" are groups of firms based on their market capitalization in the beggining of 2020. The groups include firms in the bottom three, the middle four and the last three market capitalization deciles.

Table 2: Monthly Statistics

	Both Transactions	Purchases	Sales
Total			
# of Trades	26,51	14,24	12,27
Fraction	0,91	0,95	0,93
January			
# of Trades	4,24	2,33	1,91
Fraction	0,29	0,49	0,46
February			
# of Trades	9,29	4,34	4,95
Fraction	0,63	0,71	0,76
March			
# of Trades	5,33	2,90	2,43
Fraction	0,38	0,56	0,54
April			
# of Trades	3,10	1,76	1,34
Fraction	0,21	0,37	0,40
May			
# of Trades	4,55	2,91	1,64
Fraction	0,31	0,50	0,53
June			
# of Trades	0,01	0,00	0,00
Fraction	0,00	0,00	0,00

The table reports summary statistics per month of insider trading for all S&P 500 firms during january to june 2020. Excleded from the sample are shares that doesn't appear in CRSP/Compustat merged "Security Daily" dataset for the period. "Purchases" includes all types of aquiering of shares. "Sales" includes all types of disposal of shares. "Fraction" represents the fraction of firms with at least one trade of each type. "# of trades" refers to the average number of trades per company for the 6 month period. "Small", "Medium" and "Large" are groups of firms based on their market capitalization in the beggining of 2020. The groups include firms in the bottom three, the middle four and the last three market capitalization deciles.

Figure 1: Aggregated number of insider trades per day of the sample firms
The figure presents the total number of insider transactions performed each day during the period of January - June 2020, for the 494 firms included in the sample. Transactions refers to non-derivative transactions, purchase and sell orders, reported by Form 4 filings to the SEC. The figure only shows the dates up until the beginning of June, since no transactions under the mentioned conditions were reported for the subsequent dates.



Moreover, we find in the results in Table 1 that insider trading is more frequent in larger companies (29,03 per six months) compared to smaller ones (25,66 per six months), which confirms our (1) hypothesis. This could be explained by bigger firms having a larger headcount and hence have more insiders that can trade their own company's security. Another identifiable trend that can be derived from the results displayed in Table 1 is that the fraction of insider sales and purchases is the same across size groups, while purchases exceed sales when it comes to the amount of trades. The gap between the number of insider purchases and sales becomes more narrow for larger firms compared to smaller companies. Finding the reason behind why insiders sold or purchased stock during the spring of 2020 is not the purpose of this thesis, instead our aim is to investigate *how* insiders acted during the Coronacrash and how their trades were perceived by- and performed on the market.

As seen and displayed in Table 2, the data confirms our third (3) hypothesis about an insider trading peak in February/March of 2020, in connection to the Corona Crash. These results can also be seen in Figure 1. Compared to the preceding and following months, there was an abnormally high insider trade frequency in February (over double the number of trades in January) which is the month when COVID-19 had started to spread across western countries, including the USA, and lockdowns and other restrictions were imposed over several countries (Sencer, 2022). This is in line with the findings of Marin (2013) who found that a peak in insider sales often precedes a financial crisis. However, while Marin found that this peak often occurs several months before a financial crash, our data points at increased insider activity just weeks before the crash. This could suggest that in times of crisis, the time advantage held by insiders gets smaller and that insider sales could be seen as informative of the development of the stock in the upcoming weeks, not months into the future. Moreover, Table 2 also confirms our second (2) hypothesis, with February being the only month where the number of insider sales exceeded the number of purchases. After February, insider purchasing once again overtook insider selling.

While there was insider trading of both sorts in only 29% of our sample firms in January, there were insider trades of both types, purchases and sales, happening in over 60% of our sample firms in February. In March, the insider activity dropped again, to further decline in April and then increase again in May. Against that background, we can conclude that insider trading happened across many more companies right before the crash compared to after the crash. The deviating numbers in June can be explained by the trade-stop occurring in the summer months. In summary, all of our hypotheses were confirmed by the sample data.

The results accounted for in Table 2 are in line with what (Marin, 2013) found when investigating insider trading taking place around financial crashes. The author found that insider sales reach their peak in the time preceding a financial crash, and that insider purchases tend to reach their peak right before a big increase in the stock's price. In Marin's findings however, they concluded that insiders tend to reach the peak of selling several months prior to the drop of the stock price. The reason behind this is hypothesized in the article to be because of insiders being prohibited to trade on non-public information, and in order to avoid SEC scrutiny they execute their trading orders many months ahead of an announcement that will impact the stock price.

In our findings, insider trading and foremost insider selling reached its peak in February 2020, only one month before the Coronacrash of 2020 began (Mazur et al., 2020). A plausible explanation for the discrepancy in our findings compared to Marin's (2013) findings could be explained by the different nature of our research compared to Marin's (2013). A pandemic like the one experienced in 2020 will have a ubiquitous impact across all aspects of human activity, rendering changes to the economic landscape from one day to another. This gives rise to drastic revaluations of future earnings of companies in a way that could not be predicted several months earlier by insiders. As per our results, insiders in our sample firms were still selling off their assets prior to the actual crash, i.e. in February, but due to the paradigm-shifting nature of a deadly pandemic, the time advantage that insiders have had can have become much shorter compared to under other circumstances, such as the ones under which Marin (2013) performed his studies.

Another reason why the above theory may hold true is linked to the research on insider trading made by Meulbroek (1991). Meulbroek found that the SEC generally investigates insider purchases to a greater extent than it goes after and prosecutes insider selling that has been made on non-public information. Meulbroek found that 87% of insider trading cases filed by the SEC between 1980 and 1989 concerned insider purchases. Marin (2013) reached similar findings on sample data during the period 1995-2002. Considering that February was the only month where insider selling exceeded insider purchases, and that the level of sales was >200% higher compared to all other months in our sample period except one, our data may suggest that insiders may not worry and hence not hesitate as much when selling off their own stock compared to when they are about to purchase that same stock on non-public information. Since the COVID-19 pandemic created a lot of uncertainty during the spring of 2020, it can also have been used as a cover for insiders to sell off their stock, when the real decision base for the sale might be of other, non-public and thus illegal grounds.

5. Trading period return

Table 3 presents the abnormal return for the 5 days following an insider transaction in our sample and aims to measure the market reaction following the announcement of the insider trade, as it is reasonable to assume that the information about the trade reaches the market within these five days. In accordance with the methodology used by Lakonishok and Lee (2001) we calculate daily abnormal return for the stocks following an insider trade and sum these over the 5 days, which is what is presented in Table 3. Abnormal return is calculated by subtracting the equally weighted sample return from the individual stock return. Companies are divided into size categories on a market capitalization basis. The segments are determined as described in the introduction with the bottom and top three deciles being the "small firms" and "large firms" categories, while the middle four deciles constitute the "medium firms" segment. Regarding the division of companies into B/M groups, the same

Table 3: Trading period summed abnormal returns, %

5 days sum of daily abnormal returns starting on the transaction date

	Total	Low B/M	Medium B/M	High B/M
Total				
Purchases	-0.28	-0.05	-0.34	-0.37
Sales	0.20	0.35	0.22	-0.05
Small firms				
Purchases	-0.25	-0.27	-0.24	-0.24
Sales	0.40	0.51	0.39	0.30
Medium firms				
Purchases	-0.14	0.20	-0.03	-0.51
Sales	0.19	0.41	0.37	-0.35
Large firms				
Purchases	-0.46	-0.16	-0.90	-0.34
Sales	0.07	0.26	0.16	0.04

The table reports the average abnomal returns around the transactions dates of each insider trade, for period of January to June 2020. Abnormal returns are reported as the sum of the daily abnormal returns over a five-day period starting from the transaction date. Daily abnormal return is calculated by subtracting the sample equally weighted return from the daily return of each stock. Small, Medium and Large firms refere to the firms in the bottom three, middle four and top thrre deciles of the sample based on market capitalization. Low B/M, Medium B/M and High B/M firms referes to the firms in the bottom three, middle four and top three book-to-market value deciles.

methodology has been followed, referring to the use of deciles, where the bottom three deciles constitute the "Low B/M" segment and so on. The top row shows the results in terms of abnormal trades made in firms with different book-to-market equity values.

Our first (1) hypothesis is that if the market is semi-effective (meaning that all info except insider, non-public information is priced into the security), and an insider purchase (sell) is a positive (negative) signal to outsiders then the market would react to the purchase (sell) signal by following and pushing the stock price upwards (downwards) causing positive (negative) short-term return. However, we forecast the tendencies to be clearer for the purchase transaction than the sell transactions, as sales is not an as clear signal due to the possibility of it being caused by differing incentives. A contradictory hypothesis is presented as our second (2) one, which depends on the rejection of the first one, and forecasts insider purchases (sales) to be surrounded by negative (positive) returns. The hypothesis is based on an assumption of low market efficiency and the signals not being followed by the market. In-line with the weak form of the efficient market hypothesis, the insiders would then buy shares when they deem them undervalued by the market, with the belief that they will earn money on a later increase in share price induced by factors currently ignored by the consensus. Insider purchases (sells) should therefore be surrounded by days of negative (positive) return, when the stock is performing poorly, as long as the market does not follow the insiders pushing the price upwards (downwards).

The results show that insider purchases were surrounded by negative abnormal returns on average (-0,28% for the 5 days following the transaction) and sales by positive abnormal returns on average (+0,20% for the 5 days following the transaction), causing us to reject the first (1) hypothesis. The results are rather in-line with the second hypothesis, indicating that the market was ineffective and the insiders trading based on the weak form of the EMH. The aggregated abnormal returns were close to zero across all firm sizes and B/M groups. All groups of insider purchases were followed by average negative abnormal returns for the insider except for in medium-sized firms with low B/M-value. On the sales side, all sales generated average positive abnormal returns around the trading date except for medium-sized firms with high B/M-value and large firms with medium and high B/M-value.

Concerning market efficiency, Busse & Green (2002) showed that news nowadays can be incorporated in a stock's price within a matter of seconds. This means that if insiders do have more information than external investors, stock prices should surge after insider purchases and the contrary for insider sales. Considering that we are looking at returns over a period of five days as presented in Table 3, it is possible that other news beyond the insider trade had an impact on the stock in any direction, hence creating noise that blurs our results.

Another implication of the results shown in table 3 are the implications of these insider trades as signals to external investors. If the market trusted insiders actions as guidance for their own investment decisions, we should expect the stock price to increase after a trade, with potential to beat the index development during these days. What our data suggests is that the market did not perceive insider trades as powerful signals during the COVID-19 pandemic, or at least did not react to the information efficiently, which was somewhat expected considering the general uncertainty brought about by the pandemic.

The market reacts stronger to purchases compared to sales as there can be several reasons behind an insider selling stock, but the main motivation to buy a stock must be to make money, which is something that Lakonishok & Lee (2001) also point out. Our sample data further suggests that there wasn't any substantial difference in scrutiny of smaller firms compared to larger firms during the pandemic. As seen in Table 3, firms of all sizes show abnormal returns close to zero around an insider trade. Except for Low B/M, medium-sized firms, there were no purchasing insiders that beat the market, while many sellers timed and beat the market, which is shown by these insiders yielding abnormal returns above zero. This conclusion has its limitations however considering our sample consists of the S&P 500, i.e. USA's largest and most scrutinized companies. All in all, our sample suggests that the market more or less ignored insider trades across all firm sizes during the Covid-19 pandemic, which is something that can be concluded considering that the miniscule abnormal return is uniform across all firm sizes and firm characteristics. This is aligned with the results of Seyhun (1986), Pascutti (1996) and Lakonishok & Lee (2001) on their research on insider trading under "normal" conditions.

6. NPR decile portfolio performance

Table 4 presents the performance of different NPR portfolios. The portfolios were formed based on the net purchase ratio of the sample companies, over the six month period. Portfolio 1, "Lowest" consists of the firms in the lowest decile based on NPR while portfolio 10, "Highest", consists of the highest decile. The table presents 6 months, 12 months, 18 months and 20 months ("Until now") post holding period raw returns, starting from the NPR portfolio formation date. It also presents the 12 months post holding period abnormal return, calculated as the raw return minus the equally weighted raw return of the sample, for the period. 6 months, 12 months and 24 months prior raw returns are also reported, with the aim of controlling form contrarian strategies. Lastly, average NPR, book-to-market value and market capitalization for each portfolio is presented, together with the number of firms included in each group. Results are also shown for the sample firms with no insider activity, "No", and for the sample firms divided into "Positive" and "Negative" NPR.

Our working hypothesis is that insiders should have better insight into the fair valuation of their stock compared to the average external investor and hence better decision basis for when to sell or buy the stock. As a result of the high uncertainty caused by the pandemic, connected high volatility of the market and panic reactions of the average investor, insiders should have an increased information advantage and the ability to make profitable decisions. Thus, low NPR-firms should show lower raw returns and negative abnormal returns and firms with high NPR higher raw returns and positive abnormal returns, since low NPR represents extensive insider selling and high NPR extensive insider purchasing during the six months period.

The results in Table 4 reveal that insiders in the highest NPR portfolio earned the highest post period raw return for all holding periods; between 33% and 36%, pointing towards the hypothesis being true. Likewise, the lowest NPR portfolio was among the lowest performing for all post-formation periods. For the intermediate NPR portfolios, the results are not as clear. Considering abnormal return, it is possible to see that the lowest portfolio did, as expected, have negative 12 month abnormal return. Indicating that insiders did well in selling the securities. For the highest NPR portfolio, the 12 month abnormal return was positive and also the highest, indicating that these insiders also made profitable decisions. However, as for raw returns, there is no clear linear correlation between NPR and abnormal return for the other portfolios. The interpretation of these results is that when insiders do buy (sell) substantially more than they sell (buy) in aggregate, it is a reliable signal of future gains (downturns) on the stock. However, unless NPR is very high or low, the signal might not be as reliable. Our first hypothesis is hence confirmed by our sample data, albeit with the notion that it is most reliable as an indicator in extreme cases, NPR-wise.

Another interesting finding in Table 4 is that the average market capitalization of the high-NPR firms is the lowest in the sample, while the average market capitalization of the low-NPR firms is the highest. Considering that the high-NPR firms had the largest abnormal return, this could hint about the market being more efficient (Fama, 1970) for larger firms compared to smaller firms, making it more difficult to earn an abnormal return in these securities. A possible reason for this being that larger firms are more closely followed. It also tells us that insiders bought more (relative to sales) in smaller companies than in larger ones, hinting about insiders having a greater information advantage in smaller firms compared to in larger ones.

Table 4: Performance of portfolios based on insider trading, %

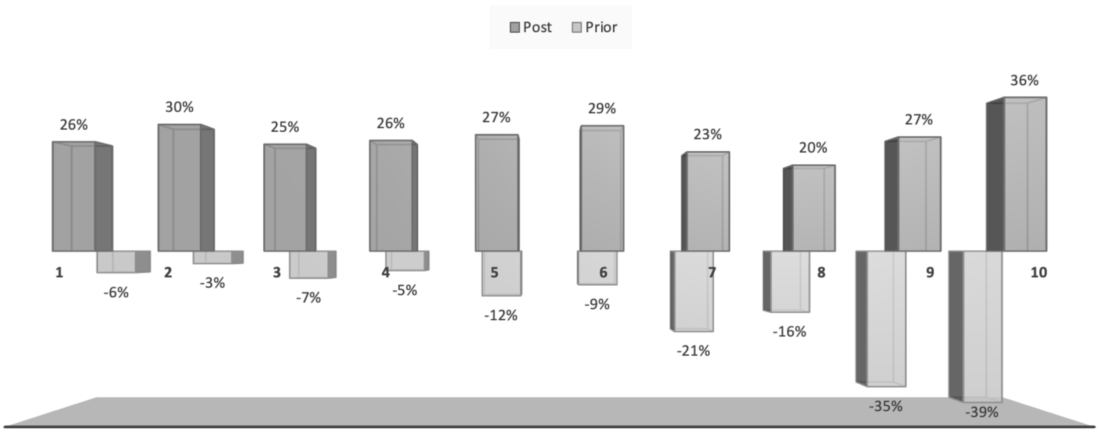
	Lowest	2	3	4	5	6	7	8	9	Highest	No	Positive	Negative
+6m	21.90	33.16	21.53	23.73	17.85	24.00	23.91	22.44	21.74	33.15	33.07	24.19	24.69
+12m	25.65	29.71	25.08	25.98	27.30	29.41	29.41	20.16	26.77	36.08	35.28	26.82	26.68
+18m	29.74	35.57	25.12	31.86	31.51	31.38	31.38	24.14	28.37	37.09	34.46	29.56	30.74
Until now	22.15	28.84	18.65	26.25	26.48	24.54	24.54	18.95	26.01	36.8	27.92	26.03	24.08
AR +12m	-0.46	3.64	0.95	1.25	0.96	3.39	-3.98	-6.52	-1.96	5.22	4.34	-0.96	1.51
-6m	-0.23	4.52	-5.44	-7.97	-10.47	-8.55	-13.34	-18.14	-28.86	-28.64	-14.53	-18.65	-1.93
-12m	-5.55	-3.23	-6.99	-5.00	-11.51	-8.65	-20.73	-15.76	-34.92	-39	-18.76	-22.31	-5.21
-24m	-7.63	4.22	-0.85	4.77	-3.54	-2.24	-22.60	-10.58	-36.49	-46.54	-33.95	-21.42	0.58
NPR	-0.71	-0.37	-0.21	-0.09	0.04	0.15	0.29	0.43	0.61	0.89	-	0.42	-0.33
B/M	0.26	0.30	0.24	0.30	0.40	0.31	0.43	0.40	0.40	0.46	0.59	0.41	0.28
Mkt cap	74943	54543	52514	61521	54966	68613	47848	57331	45098	37301	37301	51456	60835
# Firms	50	47	46	52	50	42	48	55	44	45	15	266	203

The table reports the performance of different portfolios during respective holding period. The portfolios are formed at 2020-07-01 and bases on the net purchase ratio (NPR) of each company during the previous 6 month period, January to June 2020. NPR is calculated as the number of purchases minus the number of sales divided by the total number of insider transactions. The 10 portfolios, "Lowest" to "highest" represents firms in different NPR deciles. In the formation of the 10 portfolios only firms with at least one insider transaction during the six month period are used. "Positive" ("Negative") includes the firms with positive (negative) NPR during the six month period. "+6m", "+12m", and "+18m" present different post holding raw returns. "Until now" presents the holding period raw return from the formation date until 2022-02-28. "AR+12" is the average abnormal return calculated by subtracting the equally weighted average annual return of the firms in the same size and B/M quintiles as the corresponding firm. "-6m", "-12m" and "-24m" represents priod holding period returns. "NPR" is the average net purchase ratio of the firms in each portfolio. "B/M" is the average book-to-market equity ratio. "Mkt cap" is the average market capitalization in million USD. "# Firms" is the number of firms included in each portfolio.

Moreover, Figure 2 illustrates annual raw return both post- and prior to the formation date, across all NPR portfolios. As seen in Figure 2, the highest NPR portfolio had both the worst track record and the best post annual return, meaning the group of companies where insiders bought the most in relation to insider sales were the firms that had the worst stock price decreases in the past was and also the largest stock price increase after the formation date. Figure 2 showcases the correlation between prior- and post-insider trade performance of our NPR portfolios. What becomes evident when looking at the figures is that insiders are contrarian investors that prefer to purchase stock whose prior stock performance has been bad. They are moreover successful in predicting the future stock price development of these stocks, as shown by these NPR portfolios' return. Whether this is a predictive ability caused by greater understanding of firm fundamentals or is a result of a contrarian strategy ican not be fully explained by these figures, and should therefore be kept in mind.

Figure 2: Prior and post annual raw return of net purchase ratio portfolios

We form 10 portfolios based on the number of insider transactions made in the respective companies during our sample period. We only include those firms that have at least one insider transaction during the sample period. NPR is the number of insider purchases minus the number of sales divided by the total number of insider transactions. "Prior" refers to the average one-year holding period return before the decile formation date. "Post" refers to the average one-year return starting from the decile formation date.



Against the above background, we can conclude that the data points towards insiders being able to predict future market movements also under a financial crash (in our case, the Corona crash of 2020), which is aligned with the findings of Seyhun (1998, 1992, 1988). Seyhun found that stocks that declined more during a financial crisis were the same stocks where the most bought by insiders. He also showed that the stocks that were bought the most during a crisis were the same stocks that generated the largest positive return following the crisis. The same is found for our sample firms as shown by Figure 2.

Lakonishok, Shleifer & Vishny (1994) found an inverse correlation between B/M-value and long-term past stock performance. This holds true also for our sample firms as seen in Table 4. The reasons behind this can have many roots according to the authors. A firm with low risk and whose future cash flows are discounted at a low rate would be low B/M, as well as a firm that are overvalued or have a lot of intangible assets that are not reflected in the accounting book due to R&D being expensed. In accordance with this finding, high NPR firms have higher B/M-values while low NPR firms show lower B/M-values, which also holds true for our sample if comparing the highest NPR decile with the lowest NPR decile.

One possible explanation for the clear positive trend in returns for high NPR firms is that purchasing insiders really do have an ability to predict future stock price development, and were able to do so during the COVID-19 pandemic. The conclusion reached by Lakonishok & Lee (2001), that insider buys were found as more informative by the market compared to sales, is something that according to our sample data also holds true under the Corona Crash of 2020. However, comparing our results to the ones found by Lakonishok & Lee, many of our sample firms experienced negative returns prior to the insider trade while their sample firms all showed positive returns also prior to the insider trades. It was however not unexpected that the -6m, -12m and -18m return were negative as the end date for thesee return measurements was the 30th of June 2020, i.e. after the worst market dips caused by the COVID-19 pandemic, meaning many stocks had seen big downturns by then. In total, this shows that the signals sent to external investors by inside traders follow the same pattern under crisis as they do under normal circumstances, but that they are reinforced by the crisis and that the results become more extreme.

7. Performance of different size and B/M groups

Previous research has shown that abnormal returns are dependent on firm characteristics. Some investing strategies are for example claimed to work better in smaller stocks compared to larger stocks (Chopra, Lakonishok and Ritter (1992)). The findings are consistent with the hypothesis that the efficient market hypothesis (Fama, 1970) works more efficiently for larger stocks compared to for smaller stocks. The reason behind this is assumed to be that larger firms are under more scrutiny than smaller firms (Lakonishok & Lee, 2001). In table 5 we aim to examine these relationships. In order to investigate the relationship between stock return, firm characteristics (B/M-value) and firm size (market capitalization), we calculate abnormal returns for firms in differe nt size groups, B/M groups and NPR groups with the lowest three deciles of each denoted as "Small", "Lowest B/M" and LNPR, respectively. The middle four deciles of each type are denoted "Medium", "Medium B/M" and "MNPR", respectively. The highest three deciles are denoted as "Large", "Highest B/M" and "HNPR", respectively. Averages are shown for the return of each group. This time, the abnormal return is calculated as the return of the stock minus the equally weighted return of the stocks in the same B/M and size quintiles, in order to further investigate the relationship. The group of firms with no insider trading activity, and thereby no NPR, are presented under in the "No" columns.

In accordance with previous research, we hypothesize that it should be possible to determine patterns across size and B/M groups, as the different characteristics have a possibility of correlating differently with returns as well as insiders information advantage. High B/M-value means that the market values a company's equity cheaply compared to the book value of the equity. Our hypothesis is that high B/M firms yield lower abnormal returns compared to low B/M firms.

In table 5 abnormal returns are presented on a six-month basis, a 12-month basis, an 18-month basis and 20 month basis (from the formation date until now). For comparison, 12 month post formation date raw return is also included. Looking at the total result of the statistics, we can conclude that there is no clear correlation between B/M ratio and abnormal return in these periods in our sample. In other words, our above-mentioned hypothesis is rejected, meaning the EMH does not seem to work better for larger companies during times of crisis.

Only in the mid-cap segment does the HNPR portfolio outperform the LNPR portfolio. For large firms, the HNPR portfolio largely underperforms compared to the LNPR and MNPR portfolios, which is consistent with Lakonishok & Lee's findings. Lakonishok & Lee (2001) suggests that the reason behind this is that larger companies put more efforts into discouraging illegal insider trading by using strict and extensive compliance policies, which in turn should have the consequence of disabling insiders from earning abnormal returns from trades made on non-public information.

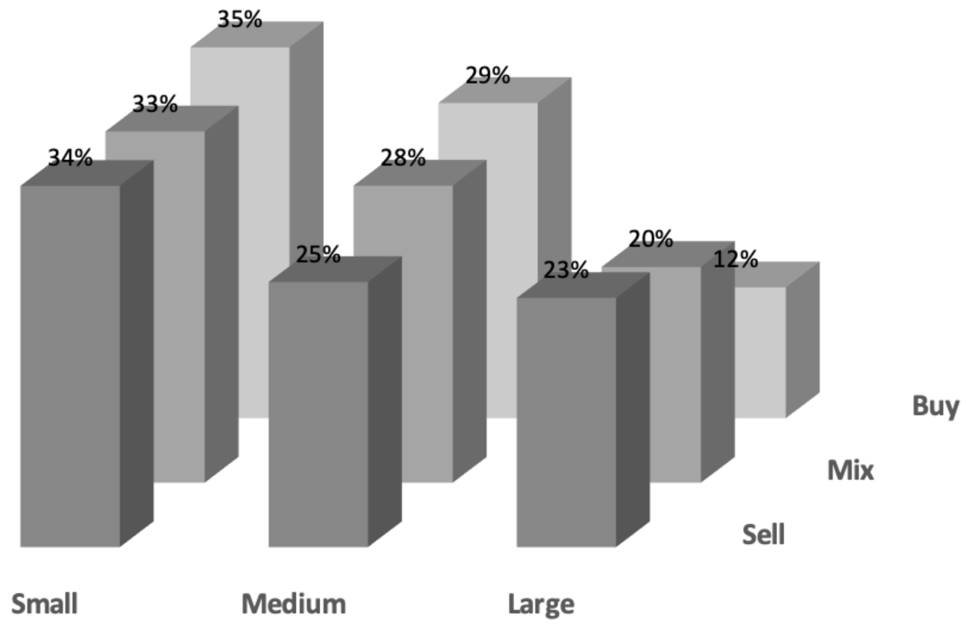
Extending these findings, Figure 3 graphically presents the one-year postformation period returns across different size- and NPR groups. One trend that can be identified in Figure 3 is that there was an inverse correlation between firm size and raw returns during our sample period. We also find that for small and medium firms, firms with high NPR (HNPR, Buy) had higher post-formation year returns than the ones with medium and low NPR. This indicates that the insiders made informed and profitable decisions in these two size groups. The pattern does not hold for large firms, where the HNPR firms generated the lowest return. A possible explanation can again be the fact that larger

Table 5: NPR portfolio performance in different size and B/M groups, %

	Lowest B/M				Medium B/M				Highest B/M				Total			
	LNPR	MNPR	HNPR	No	LNPR	MNPR	HNPR	No	LNPR	MNPR	HNPR	No	LNPR	MNPR	HNPR	No
Small																
12m	26	22	43	79	39	31	32	-	46	39	3	31	34	33	35	39
AR+6m	-5	-16	-6	97	12	-3	0	-	6	0	-3	-16	4	-5	-2	3
AR+12m	-8	-6	9	45	6	-2	-1	-	7	-2	-1	-10	1	-3	-1	0
AR+18m	-9	-6	11	41	8	-3	-1	-	6	0	-2	-9	1	-3	-1	0
AR Until now	-13	-6	14	42	10	-5	2	-	4	0	-1	-20	0	-3	1	-10
Medium																
12m	21	26	17	14	28	25	28	15	23	32	41	41	25	28	29	32
AR+6m	1	2	-5	1	5	-1	4	-14	-8	-4	8	18	1	-1	3	10
AR+12m	-2	4	-6	-11	6	1	5	-11	-8	0	5	13	0	1	2	5
AR+18m	0	9	-10	-23	6	3	0	-9	-10	2	5	5	1	4	-1	-2
AR Until now	-2	10	-9	-20	5	2	0	-14	-9	3	8	3	0	4	0	-4
Large																
12m	22	19	3	-	22	16	13	41	29	31	25	29	23	20	12	33
AR+6m	1	-2	-2	-	-4	0	5	11	2	3	-8	-6	0	0	-1	-1
AR+12m	4	0	-16	-	4	0	-5	34	-2	0	-3	1	3	0	-9	12
AR+18m	2	-2	-10	-	3	-2	-1	31	0	-3	-2	4	2	-2	-5	13
AR Until now	2	-3	-9		2	-1	-2	33	-1	-5	3	1	2	-3	-3	11
Total																
12m	22	23	13	46	30	23	27	28	31	34	36	35	27	26	27	35
AR+6m	-1	-3	-4	49	5	-1	3	-2	-1	-1	0	-2	1	-2	0	5
AR+12m	-1	0	-9	17	5	0	0	12	-2	0	1	1	1	0	-1	4
AR+18m	-2	1	-8	9	6	0	-1	11	-3	1	1	-2	1	0	-2	1
AR Until now	-3	1	-7	11	6	0	0	9	-3	0	3	-8	0	0	0	-3

The above table reports the abnormal return of insider trades in our sample companies which here have been categorized depending on market capitalization and B/M value. The bottom three deciles when it comes to market capitalization are allotted into the category "small". The four middle deviles constitute the "Medium" segment while the top three deciles are included in the "Large" category. The same methodology has been followed for the B/M categorization, but with book-to-market ratio instead of market cap as fundamental divider. In each subsegment we have further granulized the company division by classifying our sample companies depending on the their net purchase ratio. The three deciles with the lowest NPR are put into the "Low" NPR group, above shown as "LNPR". The four following deciles make up the "MNPR" group and the top three deciles are in the "HNPR" layer. The "No" column reports what percentage of our sample that did not have any trades in each period.

Figure 3: Post annual raw return in % of different size and NPR groups.
We form 10 portfolios at the end of June each year based on the net purchase ratio (NPR) of each company. We calculate NPR, the number of purchases minus the number of sales divided by the total number of insider transactions. "Insiders" include managers, board members, shareholders of >10% and anyone else deemed to have access to non-public information about the company. We use only firms with at least one insider transaction during our sample period when forming the 10 portfolios. "Sell" represents the lowest three NPR deciles, " Mix" represents the middle four NPR deciles, and "Buy" represents the top three NPR deciles. Bars designated "Small", "Medium" and "Large" comprise the bottom three, the middle four and the top three deciles, respectively, These deciles are based on market capitalization. We plot post-one-year holding period returns, which are equally weighted average returns of the firms in each group, for different size and NPR groups.



firms are under higher scrutiny causing them to be more fairly priced and insiders to have less of an information advantage.

Contrary to the findings of Lakonishok & Lee (2001), we do find major differences between the HNPR and LNPR portfolios across B/M groups. We detect the overall single biggest spread in annual abnormal return (AR+12m) between HNPR and LNPR (20%) for large, low B/M stocks, which is the segment of large growth stocks, such as Twitter, Meta and Microsoft. What is interesting is that it is the HNPR that has a negative abnormal return of -16% while the LNPR portfolio performed an abnormal return over the next twelve months of 4%. This suggests that insiders definitely were not able to predict long-term stock price development. In line with the above given argument, this finding suggests that insiders had no edge over other investors, which is supported by the notion about the efficient market hypothesis [Fama (1970)], but could also be explained by the price momentum [Jegadeesh and Titman (1993)] that suggests that stocks that perform well or poorly continue to do so. For smaller, low B/M firms, insiders do seem to have an advantage over the market as the HNPR portfolio was able to generate a 9% abnormal return over the post formation year (AR+12m). This makes sense, considering the assumption that larger firms are under greater scrutiny than smaller ones.

We detect another finding contrary to a pattern found by Lakonishok & Lee (2001) among the small cap, high B/M firms – so-called value stocks. These value stocks are usually considered "cheap" and hence, insiders tend to buy these stocks (Lakonishok & Lee, 2001). They are considered cheap since the valuation of these companies is below the value of the firms' assets. While Lakonishok & Lee found that insider sales in this firm category was followed by largely negative abnormal returns, our sample shows that a sale of these stocks was followed by a positive abnormal return (7%). The abnormal return is positive both on a six-month basis as well as in a longer time horizon. This does not apply for larger firms, where the LNPR portfolios (i.e. where insiders have sold off) show negative abnormal returns on all time frames. This indicates that insiders who were selling in small sized stocks companies were unsuccessful in predicting an upcoming downturn in stock price for their companies during the pandemic while insiders in large companies were more successful in doing so. Lakonishok & Lee found as previously mentioned that the informativeness of insider sales decreased the larger the company was. Our findings suggest that even for small firms, the informativeness seems to be low.

In summary, our data suggests that insiders in small companies were successful in predicting price upswings but not downturns, while insiders in larger companies were not very successful in predicting neither stock price decreases or increases.

8. Performance in different sectors

We sought to broaden the potential insights in this thesis regarding insider trading by adding an angle of approach not used by Lakonishok & Lee in their 2001 paper "Are Insider Trades Informative?". The reason behind including this segment in the thesis is to complement chapter 7, which investigated firm characteristics on a size- and B/M level. This following chapter will endeavor to detect abnormal activity as per NPR scores, raw returns and abnormal returns in different sectors, all showcased in Table 8. The sectors included are the 11 sectors of the GICS sector classification.

Our main hypothesis is that industries with high average NPR will demonstrate higher average abnormal return than industries with low average NPR. This would be in-line with earlier hypotheses expecting high NPR firms to outperform low NPR firms, if insiders indeed have an information advantage. Our second hypothesis is regarding fluctuations between sectors. We believe it possible for the Health Care and Consumer Discretionary sectors to show higher insider trading activity, caused by them being abnormally affected by the pandemic itself and the economic downturn, respectively.

Table 6 reports the performance of different NPR portfolios across different sectors, given in the left column. In the table, both overall return and abnormal return is presented alongside the number of firms included in each portfolio. The average NPR was negative for the Information Technology sector, Communication Services and Real Estate, meaning those experienced a lot of insider sales, relative to other industries. The industries with the highest NPR were the Materials, Energy and Financial sector. This means that insiders were purchasing a lot in companies with business in the materials industry, energy and financials during our sample period. What is interesting to point out is that the sector that one may think of as most concerned by an ongoing pandemic, the health care sector, would be in one of the extremes when it comes to average NPR. Nonetheless, our sample shows that the average NPR in the health care sector was 0,003 which is the second closest to zero among our sample industries. The consumer discretionary sector did not show a specifically high or low NPR either, although higher than the healthcare sector. This indicates that there was mixed sentiments whether to sell or buy among the insiders in both these sectors, which for the health care sector could be explained by the uncertainty revolving around an eventual vaccine and how the healthcare sector would be impacted by the pandemic in general. Of course, there may also be outliers in our data that could weigh the industry average to a certain direction, such as a vaccine-finder candidate like Pfizer or an outperformer within consumer discretionaries.

Looking at how the different sectors have performed compared to index, we evaluate abnormal returns per industry for different holding periods, which is calculated by subtracting the equally weighted average of our sample firms from the return of each stock, before averaging for the different sectors. Looking at the abnormal return from the formation data and up until now,

Table 6: NPR portfolio performances in different sectors, %

		R6	R12	AR6	AR12	AR18	ARUntil Now	#Firms	Average NPR
Communitcation Services	LNPR	25,36	26,06	1,00	-0,68	-14,17	-21,97	10	-0,134
	MNPR	28,89	26,25	4,53	-0,49	-9,92	-3,69	7	
	HNPR	36,49	38,34	12,13	11,60	5,44	12,50	3	
	No	32,15	40,56	7,79	13,82	2,14	5,26	5	
Consumer Discretionary	LNPR	43,40	36,44	19,04	9,70	9,16	8,22	16	0,132
	MNPR	32,23	31,70	7,87	4,96	8,77	3,10	20	
	HNPR	41,16	37,61	16,80	10,87	6,38	6,06	22	
	No	89,67	59,44	65,31	32,70	32,87	27,59	2	
Consumer Staples	LNPR	15,17	10,99	-9,18	-15,75	-12,60	-14,30	7	0,070
	MNPR	13,38	17,54	-10,97	-9,20	-10,60	-4,36	15	
	HNPR	1,93	-1,33	-22,43	-28,07	-31,01	-22,09	8	
	No	9,38	18,10	-14,98	-8,64	-15,02	-18,81	2	
Energy	LNPR	25,50	49,74	1,14	23,00	27,53	43,13	4	0,325
	MNPR	5,81	39,34	-18,55	12,60	6,77	24,45	7	
	HNPR	6,51	29,42	-17,85	2,68	3,01	19,09	10	
	No							0	
Financials	LNPR	17,98	23,40	-6,38	-3,34	1,91	5,72	10	0,213
	MNPR	29,06	37,73	4,70	10,99	12,94	15,44	29	
	HNPR	31,28	38,30	6,92	11,56	10,55	15,80	24	
	No	24,50	38,02	0,14	11,28	13,88	16,41	4	
Health Care	LNPR	18,00	23,57	-6,36	-3,17	-6,20	-8,31	20	0,003
	MNPR	16,80	22,92	-7,56	-3,82	-1,48	-1,63	30	
	HNPR	20,22	19,91	-4,14	-6,83	-8,82	-8,20	11	
	No	19,59	9,61	-4,77	-17,13	-17,33	-32,85	2	
Industrials	LNPR	25,22	27,92	0,87	1,18	3,59	5,37	21	0,153
	MNPR	27,11	23,65	2,76	-3,09	-3,38	-4,55	24	
	HNPR	35,84	37,51	11,49	10,77	8,61	8,68	25	
	No							0	
Information Technology	LNPR	35,68	29,72	11,32	2,98	2,72	-4,23	35	-0,108
	MNPR	25,01	26,32	0,65	-0,42	-0,61	-7,61	29	
	HNPR	20,28	18,96	-4,08	-7,78	-11,52	-16,29	10	
	No							0	
Materials	LNPR	18,28	24,64	-6,08	-2,10	-3,48	-3,77	3	0,389
	MNPR	39,05	34,33	14,69	7,59	10,62	8,68	8	
	HNPR	37,56	27,52	13,20	0,78	2,23	2,15	14	
	No							0	
Real Estate	LNPR	7,45	22,88	-16,90	-3,86	3,78	-0,78	11	-0,002
	MNPR	12,11	24,90	-12,25	-1,83	1,94	2,59	10	
	HNPR							8	
	No							0	
Utilities	LNPR	5,44	9,21	-18,92	-17,53	-15,90	-12,38	6	0,180
	MNPR	2,90	5,86	-21,45	-20,88	-17,87	-17,13	13	
	HNPR	-1,52	-18,22	-25,88	-44,96	-35,73	-35,83	9	
	No							0	

Each number is an equally weighted average of the corresponding return, for that group. Abnormal returns are calculated as the holding period return of industry (i) minus the equally weithed average return of the whole sample for that holding period. Average NPR is calculated as the average NPR of the firms in each industry with insider transactions (firms with no transactions doesnt have an NPR). R6 shows raw returns for each industry on a six-month basis and R12 shows raw returns on a twelve-month basis. "Aruntilnow" shows abnormal return until when the data of this thesis was collected, i.e. in February 2022. #Firms reports the number of sample firms that were included in the calculation of the industry averages. "No" shows the return and abnormal return of firms in each industry with no insider trades during our sample period.

table 6 shows that the sectors with the highest abnormal return are the Financial sector, the Energy sector and the Consumer Discretionary sector. The biggest losses in terms of abnormal return until now have been drawn in the Communication Services sector, the Consumer Staples sector and in the Utilities sector. However, considering *raw return* instead of *abnormal return*, denoted by R6 for six-month return and R12 for twelve-month return, Table 8 shows that raw return has been positive for all sectors across all NPR levels with an exception for High NPR-firms in the Utilities sector and High NPR-firms in the Consumer Staples sector. There is in other words no apparent correlation between NPR and returns across industries.
Apart from this, all sectors have been generating positive returns both on a six-month and twelve-month basis. Highest six-month return was given in the Consumer Discretionary industry while the highest twelve-month return was given in the Energy sector, basically confirming the results given by abnormal return. The Utilities sector generated the lowest returns both on a six-month basis and a twelve-month basis.

We can further conclude from Table 8 that superior performance by high NPR firms is not uniform across industries. It was correct in the Communications Services, Financials, Industrials and to some degree Materials industry. Hence, those are the industries where insider trades were indeed informative to external investors. As the constituents of the Communication Services, Financials and Industrials industries are all far apart in terms of firm characteristics (B/M) we cannot conclude to detect a clear pattern between B/M industries and return. Nor can we conclude that insider trading worked as an informative signal to external investors during the COVID-19 pandemic.

9. Regression Analysis

Previous to this chapter we have presented raw- and abnormal returns for firm groups depending on B/M ratio, size, industry and net purchase ratio. In accordance with the methodology used by Lakonishok & Lee (2001), we run a regression on the variables previously looked into. The purpose is to investigate whether insiders were able to predict cross-sectional returns with their trades during the COVID-19 pandemic, which may be indicative for future crises. As shown in Table 4 and Figure 2, insiders tend to buy stocks that have performed poorly in the past. As Debondt & Thaler (1985) showed that stocks that have been long-term losers in the past usually outperform past winners, we want to make an adjustment for differences in long-term returns. Contrarian strategies, as mentioned in previous chapters, target this phenomenon, and is something that insiders usually reside to, as shown by Lakonishok & Lee (2001) and Seyhun (1988, 1998). As we found in Table 6, there are big differences in returns over the period preceding the trade. Hence, when determining insiders ability to predict cross-sectional returns, we need to control for both intermediate- and long-term past performance as well as for B/M-value and size. In order to undertake this task, we use a multilinear regression approach in order to test insiders' ability to predict cross-sectional returns while assessing statistical significance.

We run a cross-sectional OLS regression (regression 1) where the dependent variable (Raw Return_i) is the raw return of the stock *i* over the next twelve months, and include robust standard errors in order to obtain unbiased standard errors on our coefficients. The explanatory variables include measures on insider trading activity and control variables. The main variable, NPR*i*, measures insider trading activity, and takes on the minimum value of minus one (-1) when insiders are only selling, and a maximum value of one (1) when insiders are only buying. The control variables used are *LBMRi* [ln(B/M)], *LSIZEi* [ln(market capitalization)] and two independent variables that capture past returns. Intermediate-term past holding return is measured by *PR12*, holding return in the past 12 months, while long-term past performance is measured by *PR24i*, return over the past 24 months. Previous research, including Lakonishok & Lee (2001), suggests that insider's ability to predict returns is greater in larger companies compared to smaller companies which is why we include a control variable for the size. In addition, differences across B/M values have shown to be of interest, explaining the LBMR control variable. Past performance control variables are included to control for contrarian strategies. We also run a regression using the same independent variables but put *Abnormal*

Return as an independent variable instead, (regression 4), in order to detect whether there are any fundamental indicators in insider trading, company characteristics and past return for a stock's ability to beat index. In all regressions we measure returns in percentages.

We run regressions, on raw- and abnormal return (regression 2 and 5, respectively), including dummy variables for strong buy- or sell-signals, similar to what is done in Lakonishok and Lee's regressions. While their buy-dummy took on the value of one (1) when NPR≥0.95, the net dollar volume traded is in the top 25% and there are at least three different insiders trading, our buy-dummy takes on the value of one (1) when NPR≥0.7. We lower the cut-off value for NPR and ignore the two other signals included by Lakonishok and Lee because of a couple of reasons. We do have a smaller sample compared to Lakonishok and Lee, which speaks for lowering the cut-off point. We also lack data on dollar volume traded as well as on individual trader identification, but the results would be interesting nonetheless as an NPR of 0.7 or -0.7 should still be considered strong signals in either direction. The goal of including these dummy variables is to capture the correlation between insider purchases or sales and stock return.

Lastly, we run regressions, on raw and abnormal returns (regression 3 and 6, respectively), with one dummy variable for all sectors except one. The goal of these regressions is to fix the results in regression 1) and 3) for industry, sector, effects. These are systematic differences between the sectors that could affect the regressions and their explanatory value.

The regressions runned on 12 months raw returns

Regression 1:

$$Raw\ Return_i = \alpha_1 + \beta_1 LBMR_i + \beta_2 LSIZE_i + \beta_3 PR12_i + \beta_4 PR24_i + \beta_5 NPR_i$$

Regression 2, with dummy variables for strong buy- or sell-signals:

$$Raw\ Return_i = \alpha_1 + \beta_1 LBMR_i + \beta_2 LSIZE_i + \beta_3 PR12_i + \beta_4 PR24_i + \beta_5 NPR_i + \beta_6 DPL_i + \beta_7 DSL_i$$

Regression 3, industry fixed effects:

$$Raw\ Return_i = \alpha_1 + \beta_1 LBMR_i + \beta_2 LSIZE_i + \beta_3 PR12_i + \beta_4 PR24_i + \beta_5 NPR_i + \beta_6 DSECTOR_i$$

The regressions runned on 12 months abnormal returns

Regression 4:

$$Abnormal\ Return_i = \alpha_1 + \beta_1 LBMR_i + \beta_2 LSIZE_i + \beta_3 PR12_i + \beta_4 PR24_i + \beta_5 NPR_i$$

Regression 5, with dummy variables for strong buy- or sell-signals:

$$Abnormal\ Return_i = \alpha_1 + \beta_1 LBMR_i + \beta_2 LSIZE_i + \beta_3 PR12_i + \beta_4 PR24_i + \beta_5 NPR_i + \beta_6 DPL_i + \beta_7 DSL_i$$

Regression 6, industry fixed effects:

$$Raw\ Return_i = \alpha_1 + \beta_1 LBMR_i + \beta_2 LSIZE_i + \beta_3 PR12_i + \beta_4 PR24_i + \beta_5 NPR_i + \beta_6 DSECTOR_i$$

Table 7: OLS regressions

Dependent variable:	Post formation year - Raw return			Post formation year - Abnomral return		
	1	**2**	**3**	**4**	**5**	**6**
NPR	-0.031	-0.097*	-0.031	-0.031	-0.096*	-0.031
	(-1.209)	(-2.184)	(-1.207)	(-1.209)	(-2.184)	(-1.207)
LBMR	0.009	0.009	0.012	0.009	0.009	0.012
	(0.799)	(0.805)	(0.978)	(0.798)	(0.805)	(0.987)
LSIZE	-0.057**	-0.057**	-0.056**	-0.057**	-0.057**	-0.056**
	(-3.278)	(-3.308)	(-3.251)	(-3.278)	(-3.308)	(-3.251)
PR12	-0.112*	-0.111*	-0.114*	-0.112*	-0.111*	-0.114*
	(-2.404)	(-2.440)	(-2.341)	(-2.404)	(-2.440)	(-2.351)
PR24	-0.055*	-0.055*	-0.047	-0.055*	-0.559*	-0.047
	(-2.043)	(-2.116)	(-1.718)	(-2.043)	(-2.116)	(-1.718)
DPL		0.096*			0.096*	
		(2.183)			(2.183)	
DSL		-0.115*			-0.115*	
		(-2.236)			(-2.236)	
Intercept	0.845***	0.847***	0.899***	0.601***	0.603***	0.655***
	(4.957)	(5.019)	(5.121)	(3.481)	(3.531)	(3.678)
Industry fixed effects	No	No	Yes	No	No	Yes
Robust standard errors	Yes	Yes	Yes	Yes	Yes	Yes
Observations	449	447	439	449	447	439

The table reprots the coefficients and t-values from ordinary least squares (OLS) regressions of post one year holding return on NPR, control variables and chosen dummy variables. T-values are presentet below each coefficient, in pharentheses. Regressions are done as robust standard errors, to adjust for possible problems conected to hetroscedacity. Panel A, regression (1) to (3), is performed on raw return. Post formation year Raw return is the holding period return of each stock, for the year subsequant to the formation date. (1) includes NPR and the four control variables. (2) includes NPR, the four control variables and dummies for strong purchase versus strong sell signal. DPL sets to 1 if NPR > 0.7. DSL sets to 1 if NPR < -0.7. (3) includes NPR, the for control variables and dummy variables for different industries to control for industry fixed effects. Panel B, regression (4), (5) and (6), is performed on abnormal returns but are otherwise identical to regression (1), (2), and (3), respectively. Post formation year Abnormal return is the abnomral holding period return of each stock, for the year subsequant to the formation date. Abnormal holding period return is calculated by subtracting the equally weighted sample holding period return from the holding period return of each stock. NPR is the net purchase ratio of each stock, calculated as net aggregate insider purchases divided by net aggregate insider trades during the six months period of January-June 2020. LBMR is the logaritm of the book-to-market equity value of each stock, as of 1st of January 2020. LSIZE is the logaritm of the market capitalization of each stock, as of 1st of January 2020. PR12 is the 12 months holding period return of each stock, up until the formation date. PR24 is the 24 months holding period return of each stock, up until the formation date. Significance codes: 0 "***", 0.001 "**", 0.05 "*".

The numbers reported in table 7 are the coefficients from our regressions, all adjusted to get robust standard errors. The numbers on top represent the different regressions made. Column 2 and 5 include the dummies for strong buy or sell signals, while column 3 and 6 include dummy variables for different industries to control for industry fixed effects. The first three columns present coefficient estimators for regressions with raw return as the dependent variable, while columns 4 to 6 report the coefficient estimators for regressions with abnormal return as the dependent variable. For the same regressions performed on raw and abnormal returns (1 and 4, 2 and 5, 3 and 6) some of the coefficients show close to identical values for some variables, which is reasonable and expected as we subtract the sample average from the individual firm returns when calculating abnormal returns.

For the main regression, (regression 1 and 4, respectively), we get significant results for company size and past return (both 12 months and 24 months). While Lakonishok and Lee (2001) got one of their most significant coefficients in book-to-market, we do not get a significant result for this variable. The fact that we do get significant results for long-term past return is contrary to the findings of the mentioned researchers. Both past return-coefficients are negative for our main regression, which means that there is an inverse correlation between past return and future return in our sample. In other words, bad past return is correlated to better future return than good past return is. This indicates a possibility to earn from contrarian strategies. Moreover, the size coefficient is negative, confirming what we previously have claimed in this thesis, that returns were larger for smaller firms compared to for larger firms. One of the most important things to point out is that we only achieve significant results for NPR when we include the dummies for strong buy and sell signals. This makes sense since by adding the dummies the data group becomes more narrow for analyzing NPR's correlation with return. When comparing the first and second regressions, we see that the introduction of dummies does not impact the size estimates nor the past return estimates, which is reasonable as insider trading does not impact the size of the company or what has happened in the past.

Looking at the second and fifth regression, where we include dummies for insider signals and which yielded significant results for our NPR variable, our NPR/B5-coefficient is -0.097, which implies that after controlling for other variables, the difference in returns between pure buyers (NPR = 1) and pure sellers (NPR = -1) is 19,4% per year in the first post formation year. The results from this regression shows how important insider activity is even during crises, and that they may be useful as signals for external traders of what is to expect next in terms of returns in times when general uncertainty is ruling on the markets. As seen in Table 7, a strong buying signal (B6) is associated with a significant excess return of almost 10% per year in times of crisis, while a strong sell-signal is associated with an upcoming downturn of -11,5% of the stock per year. The same applies for abnormal returns. What is interesting is that this goes against previous research, which suggests that selling by insiders does not predict future stock downturns. This has been motivated by insiders selling off stock in order to rebalance and diversify their portfolios in times when executive compensation increasingly gets tied to stock (Lakonishok and Lee, 2001). Our finding suggests that during the COVID-19 pandemic, insiders were able to predict future stock movements and that both insider buying and selling had useful signaling value. This is a finding that may prove useful in future research of insider trading in connection to other crises.

When we fix for sector effects, we get the results of regression 3) and 6). We can see that these are not very different from the results of regression 1) and 4), indicating that possible systematic effects within sectors did not affect our initial result significantly. For NPR, the coefficient remains the same for both the raw return and abnormal return regression. For LBMR and LSIZE as well as PR12 and PR24, there are small differences. The only variable significantly affected by the industry effects seems to be the long-term prior return, PR24, which is significant at a 5% level when not fixing for industry effects, but not significant anymore when doing so. This suggests that when taking into account the differences between sectors, the long-term prior return does not significantly affect the prediction of past returns, as suggested by regression 1) and 4).

In conclusion we can conclude that insiders successfully predicted future stock price movements during the pandemic whether it was going up or down. Moreover, using a contrarian strategy was generally a good strategy during the pandemic as past losers were the biggest future winners, and lastly we found that returns during the pandemic were greater for smaller firms

10. Difference-in-difference Analysis

We further include a differences-in-difference test in our thesis as a robustness test. This is a statistical method through which we are able to study the differential effect on a treatment group versus a control group (Angrist & Pischke, 2009). In our study, we compare the return of insiders and their predictive ability during the COVID-19 pandemic in 2020 to the return and predictive ability of insiders in 2018, before the pandemic. The 2018 returns are our control group while the 2020 returns during the pandemic constitute our treatment group. The reason we use 2018 and not 2019 as our control group is that when calculating returns after insider trades in 2019, we would have entered 2020 and hence would the results in our control group include returns during the COVID-19 pandemic, and thus not serve as a control group. Using 2018 as the control group lets us stay as close to 2020 as possible, without any effects of the pandemic. In that way, we keep surrounding circumstances as similar as possible. With that being said, 2018 was also an eventful year, with the Cambridge Analytica scandal, midterm elections that reshuffled the power in the congress while the back-then president Trump was investigated for the alleged involvement of Russia in his 2016 presidential campaign (Forbes, 2018). However, we concluded that there was no major event that would offset 2018 as a suitable year to use in our DiD analysis on insider trades and holding period returns.

Lakonishok & Lee (2001) did not include a differences-in-difference test in their study since they were not conducting research on a topic or in an environment that deviates from the normal state. Instead they studied insider trading over a long period of time. The scope of this study is in that regard quite different from Lakonishok & Lee's, as our goal is to investigate whether insider trading during the start COVID-19 pandemic differed from insider trading otherwise. This can be achieved by a differences-in-differences analysis where we will be able to compare the results in this study to trends before the dawn of the pandemic. The differences-in-difference method includes making a parallel trends assumption, which in this case means that our base assumption is that the year 2018 provides an appropriate counterfactual trend that insider trading in 2020 would have followed if it were not for the COVID-19 pandemic. In other words, our assumption is that without COVID-19, returns and predictive ability for insiders in 2020 would have followed the same trend as they did in 2018. Nonetheless, we do expect the trading behavior and results to differ.

To perform the regression, we create one dummy variable for the year concerned, which takes on the value of one (1) if the trade is made in 2020, and conversely it takes on the value of zero (0) if the trade is made in 2018. We further create another dummy variable for NPR, which takes on the value of one (1) if the NPR score is positive (>0) and takes on the value of zero (0) otherwise. Lastly, we create one differences-in-differences variable which is the product of the two above-mentioned dummy variables, concerning the year and NPR-ratio.

$DYEARi$ = 0 if 2018, 1 if 2020
$DNPRi$ = 0 if NPR $\leq$ 0, 1 if NPR > 0
$DIDi = DYEARi * DNPRi$

$$R = \beta_0 + \beta_1 DYEARi + \beta_2 DNPRi + \beta_3 DiD$$

Table 8: Difference in Difference regression

Regression on post formation annual return for 2020 versus 2018

Dependent variable:	Post formation year Raw return
DYEAR	0.159***
	(4.517)
DNPR	0.009
	(0.270)
DID	-0.007
	(-0.167)
Intercept	0.105**
	(3.226)

The table reports results for the difference-in-difference regression results on post formation annual return as the dependent variable. Annual return is calculated as the holding period return over one year following the formation date. 2020 is the treatment group. 2018 is the control group. DYEAR is a dummy variable for the year, DYEAR = 1 if the year is 2020. DNPR is a dummy variable for positive NPR, DNPR = 1 if NRP > 0. The data covers a total of 910 observations. DID is the difference in difference estimator, multiplying DYEAR and DNPR.

The result of the Difference-in-Differences regression is reported in Table 8. Results are significant for the year dummy, DYEAR*i*, suggesting that there was indeed a significant difference between the returns in 2020 and 2018. The results indicate that there was a close to 16% spread in raw twelve-month returns of the firms included in the sample in 2020 compared to in 2018. Insiders in our sample did, as the rest of the market, perform better on trades done during the 2020 crisis compared to the ones they did in 2018. However, the NPR dummy, DNPR*i*, is insignificant suggesting that these performances were not significantly caused by insiders making informed decisions. Even if considered, DNPR*i* showed a low value of 0.009, indicating that insiders on average were not remarkably good at predicting future stock return. If a variable would be positive, it would mean that it is correlated to stock return >0, and if negative it would be correlated to a negative stock price development. This result is probably blurred partly by the fact that our NPR dummy is set to 1 when NPR>0, which can be very ambiguous considering it may entail that investors have bought just a little more than they have sold. An NPR of 0.1 and an NPR of 0.95, which was used by Lakonishok & Lee as their cut-off value when determining what NPR value should be deemed a strong buy signal, are vastly different and may hence deteriorate the value of the results given by our regression. In chapter 11 we will further address our insignificant results, investigate the reason behind them, what to make of them and how future research may complement this thesis.

The DID*i* estimator, combining the effects of the DNPR*i* and DYEAR*i* dummies, is also insignificant. The coefficient is also negative, indicating that if significant it would suggest that NPR was less indicative of future year returns in 2020 than 2018. These findings conclude that based on our sample, insiders did perhaps earn higher returns following the pandemic but these were not caused by them being informed but rather by the development of the market as a whole. If the returns earned would have been results of the inder's informativeness, NPR and past return should correlate positively on a significant level, suggesting that firms with extensive insider purchasing indeed performed better over the subsequent year. This does not seem to be true for our sample. However, since the results are not significant, we cannot fully reject the possibility.

11. Discussion

11.1 Limitations

As shown in the past two chapters covering regressions and difference-in-differences analysis we did not reach any significant results on our DiD-regression beyond the year dummy, but we did manage to get some significant results on our other regressions. The following paragraphs will discuss those insignificant results and aim at derivating the potential roots to the lack of statistical power.

First off, it is suitable to summarize the differences in our research and the research conducted by Lakonishok and Lee (2001), whose methodology we to great extent have used. As mentioned in the introduction, Lakonishok and Lee looked into detecting patterns in insider trading over a period of twenty years, from 1975-1995. Moreover, they included insider trading conducted in all companies on the NYSE, AMEX and Nasdaq during this period. On the other end, we looked into insider trading during the spring of 2020, in companies that are included in the S&P 500 index. Needless to say, the scope and aim of our study caused us to conduct research on a far smaller sample than Lakonishok and Lee. This has big implications for the statistical power of the study as well as the margin of error, where the former is low and the latter greater with a small data sample. In retrospect, we could have conducted a priori determination of a sample size requirement that would have given us a high probability of getting more significant results.

When concerning the strong buy- or sell-dummies we used, the above-mentioned problem worked in combination with us applying less restrictions on the dummies. While Lakonishok and Lee had three requirements for the dummy to be activated, we only had one requirement that was substantially softer than theirs. While they required an NPR>0.95 to classify a strong buy-signal, we only required an NPR>0.7, which of course could have caused noise in our results. There is of course a possibility that there really is a difference between the populations as well as there could be correlational relationships between industries and returns, but that it exists on a much lower level or magnitude than we anticipated.

11.2 Future research

For any future research that may be conducted on insider trading during the COVID-19 pandemic or another period of crisis, or that considers using the framework developed by Lakonishok & Lee (2001), we would extend the following recommendations in order to get satisfactory and significant results:

1. Make sure to use a substantial dataset, preferably aggregate data from all companies listed at one or more stock exchanges instead of the constituents of one stock index, as we have learned that it sets clear boundaries for the reach of your research.
2. If replicating the methodology by Lakonishok & Lee, ensure the dataset includes data on all parameters needed to execute all tests that they do, as this improves compatibility.

Moreover, it is up to future researchers to complement the existing research on insider trading and this paper on insider trading during the COVID-19 pandemic. The implications of insider trading overall and especially during crises may have further implications for the efficient market hypothesis, as crises can push insiders to execute on eventual non-public information. For future research, it would be interesting to look into and conduct further research that may help explain some of the findings made in this thesis, such as that insider sales were predictive of future stock price decreases, which is contrary to what previous literature had found. Future research could help explain whether this occurrence was unique for the pandemic we experienced or that would hold true for other crises as well.

11.3 Summary and concluding remarks

With this paper we set out to investigate how insider traders acted during the beginning of the COVID-19 pandemic, when markets were at their shakiest and the future as most uncertain. In order to do so we used tools and mental models developed by previous researchers. Against the background presented in the past chapters we can conclude that insider trading did indeed intensify at the start of the pandemic, that the market did react to signals in the form of insider trading, shown by the short-term stock price changes. Moreover, we have shown that insiders usually bought the stock when the stock had performed badly, and sold their stock when the stock return was good. This last finding diverts from previous research and suggests that insider trades could have greater signaling value for external investors in times of crisis compared to under normal circumstances. Our findings also conclude that insiders in large companies have better predictive ability compared to insiders in smaller companies. Among our results we also find a significant difference in pricing of small companies and pricing of larger companies. This indicates that the biggest opportunity for externals looking to exploit insider signaling during times of crisis lies in smaller companies, as the market perceives insider signals with much less enthusiasm in these companies, even though these companies offered large returns. Another finding in this thesis was that there was a consistent trend of insiders using contrarian trading strategies also during the pandemic, which is a strategy that they also use in non-crisis times as shown by previous literature. Future research will however have to investigate whether this holds true for insider trading in other types of crises that bring uncertainty to stock markets or if this trend was unique for the COVID-19 pandemic crisis.

Albeit trying to detect any eventual insider trading across industries we did not see any clear pattern related to NPR or B/M and return across industries. In line with the conclusions reached by Lakonishok and Lee, we found that the majority of the insider trading happens in large stocks, where insider activity has limited value compared to insider trading in smaller stocks.

Perhaps the most important takeaway from this thesis is that insider trading followed certain patterns during the pandemic, which is something that may come to use for external investors in future crisis scenarios when trying to understand how to interpret insider trades for information when uncertainty is ubiquitous. Against the background presented in this thesis, we can conclude that some investors indeed were successful at predicting future stock price developments during the pandemic, with the highest NPR portfolios outperforming the lowest ones and the strong buy and strong sell dummies showing significantly positive and negative correlation with 12-month post return, respectively. Aggregate insider trading seems to have some predictive value, especially in the extreme cases, enabling external to profit off copying these trading patterns, whether it be selling off their stock or purchasing stock. This despite the fact our data suggests that in the short term, the markets to great extent ignored these signals given by insiders.

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